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On the data-driven investigation of factors affecting the need for icebreaker assistance in ice-covered waters

Cong Liu [a,*], Ketki Kulkarni [c], Mikko Suominen [a], Pentti Kujala [a,b], Mashrura Musharraf [a]

[a] *Marine and Arctic Technology, Department of Mechanical Engineering, Aalto University, Espoo, Finland*
[b] *Waterways Safety Management, Taltech/Estonian Maritime Academy, Tallinn, Estonia*
[c] *Supply Chain Management and Social Responsibility, HUMLOG Institute, Hanken School of Economics, Helsinki, Finland*

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ABSTRACT

Merchant vessels often require icebreaker (IB) assistance to create safe pathways and improve efficiency when navigating in the Baltic Sea. Since IB resources are limited, an accurate estimation on the need for IB assistance is important. Whether IB assistance is needed depends on multiple factors. While practical experience from captains is naturally a source of valuable information for the decision on the need for IB assistance, systematic analysis of the reasoning is limited. The primary aim of this paper is to holistically investigate the influencing factors and their effect on estimating the need for IB assistance through data-driven techniques. Based on a comprehensive list of potential factors, different of data such as traffic history, environmental conditions, and ship specifications are gathered to present complex navigational scenarios. Each scenario is labeled by different navigation modes (independent navigation or IB assistance), laying the foundation for influencing factor identification and effect quantification. Logistic regression is applied to evaluate the effect of the factors on the need for IB assistance. The results show that the impact of the factors is diverse, and ridged ice concentration has the most significant impact. The effectiveness of identified factors is measured by comparing it to that of the factors that have been implemented by the existing studies (e.g., the combination of ice concentration, thickness, and ship ice class, or only ship speed). By considering the factors in this study, the classification performance can be improved by at least 5.6%. The findings in this paper can provide insights for predicting IB workloads and optimizing IB resources and have the potential to support the development of an intelligent decision-support system for winter navigation.

1. Introduction

Winter navigation operations are common but complex because of the existence of ice in the Baltic Sea. There are two typical navigation modes, independent navigation and icebreaker (IB) assistance operation (Valdez Banda et al., 2016). Independent navigation refers to an operation mode where a vessel navigates independently in ice-covered water without any assistance from other vessels or IB. IB assistance is an operation where one or more icebreakers assist the merchant vessel(s) to navigate in ice-covered waters (Zhang et al., 2019). Assistance mode is critical for winter navigation safety and efficiency in the Baltic Sea. It can help reduce the risk of the ship getting stuck or getting hull damage and decrease the required fuel consumption (Bergström and Kujala, 2020; Choi et al., 2015). However, the demand for IB assistance from merchant vessels often exceeds the supply of icebreakers. One of the key estimations that IB captains need to make is whether a vessel would need assistance to proceed with the navigation, as it impacts the overall traffic flows in the area (BIM, 2020; Stoddard et al., 2016). Accurate estimation of the need for IB assistance matters for optimizing IB resources and improving the efficiency of the whole winter navigation system.

The current efforts aiming to mimic the winter navigation system in the Baltic and find out the optimal demand of IB resources mainly come from engineering simulations (Bergström and Kujala, 2020; Kondratenko et al., 2021; Kulkarni et al., 2022; Lindeberg et al., 2018). The studies describe the interaction between traffic scenarios and ice conditions using semi-empirical equations or equivalent modeling techniques. Even though state-of-the-art simulations could present components of the winter navigation system at a detailed level, there is still a significant gap between the simulation and reality due to the nonlinearity and stochastic features of the real-life system. Therefore, understanding the reasoning behind the estimation is necessary. While

* Corresponding author at: Otakaari 4, 02150 Espoo, Finland.
E-mail address: cong.1.liu@aalto.fi (C. Liu).

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Nomenclature

Variable	Definition
IB	Icebreaker
FSICR	Finnish-Swedish ice class rules
POLARIS	Polar operational limit assessment risk index system
AIRSS	Arctic ice regime shipping system
SC	Ship category
WC	Weather category
IC	Ice category
HELMI	Helsinki Multi-category sea-ice model
AIS	Automatic identification system
MMSI	Marine mobile service identity
SF	Ship factors
WF	Weather factors
IF	Ice factors
VIF	Variance inflation factor
OR	Odds ratio
ROC	The receiver operating characteristic
AUC	The area under the receiver operating characteristic curve
TP	True positive
FP	False positive
FN	False negative
TN	True negative
TPR	True positive rate
FPR	False positive rate

the operational experience of human experts is naturally important in decision-making, the reasoning behind each individual case is hidden and can vary due to human subjective knowledge. Instead of collecting individual human decisions and reasoning on board, data-driven methods can be an alternative to capture and comprehend information about complex operational scenarios by learning patterns behind the decision from the data.

To conduct a data-driven analysis on the need for IB assistance estimation, influencing factors and to what extent they can affect the need for IB assistance should be available. A considerable number of studies have directly assessed or indirectly referred to factors that indicate the need for IB assistance (Choi et al., 2015; Kuuliala et al., 2017; Lehtola et al., 2019; Lu et al., 2021; Topaj et al., 2019). While factor analysis has been done for diverse research contexts, ranging from ship performance assessment (Kuuliala et al., 2017), and route planning in ice (Lee et al., 2021), to besetment evaluation (Turnbull et al., 2019) and winter navigation system simulations (Kulkarni et al., 2022), direct and comprehensive information about influencing factors for estimating the need for IB assistance is limited. Another issue with existing studies is the restricted focus. As only a limited number of cases have been examined to draw conclusions, the generalization ability of the methods and/or the findings is limited. To enable a better understanding of winter navigation operations, an approach driven by a comprehensive, scalable dataset is needed.

To bridge the above gaps, this paper presents a data-driven framework to capture the information of historical cases and comprehend the need for IB assistance using quantitative factors. We first identify a comprehensive list of known factors that might lead to the need for IB assistance by literature search. This step is essential, as scattered information regarding influencing factors needs to be combined to provide a comprehensive and exhaustive source for all known factors. Second, using the list of factors as a guide, we explore multiple data sources to find data about the collected factors. A novel database is established to reflect operational conditions. Independent navigation and assistance operation cases are labeled in the database by a multi-step clustering method (Liu et al., 2022). This step is critical because it lays the foundation for the implementation of data-driven analysis. As a starting point, the data information in this paper bridges the gap of insufficient objective data available for winter navigation research. Finally, logistic regression model is adopted to analyze the influencing factors and quantify their effects accordingly. The study also assesses the impact of diverse conditions on the need for IB assistance regarding ships with different ice classes. Compared to the state-of-art, quantitative knowledge of the influencing factors impact becomes available in this paper. The findings can help to interpret the underlying reasons for when and where IB assistance would be needed and support IBs in estimating the forthcoming assistance workload by a data-driven approach. Therefore, the development of explainable and intelligent decision-making in winter navigation can benefit from this data-driven study.

The rest of the paper is organized as follows. Section 2 conducts a literature review to collect potential influencing factors and highlights the research gap. Section 3 proposes the approach for establishing the novel database presenting factors of both navigation modes. Then based on the database, the approach quantifying the factor effect is described, followed by Section 4 presenting results and discussions on the findings. Finally, Section 5 proposes limitations and future work, and Section 6 concludes the work.

2. Literature review for influencing factors collection

As a functional component of winter navigation, IB assistance operation has been mentioned in various research contexts. To collect a comprehensive list of factors from literature, this study focuses on the thematic coverage of IB assistance operation by grouping existing literature into the following contexts: route planning in ice, besetment evaluation, ship operability assessment in ice, and winter navigation system simulation (Liu et al., 2023). The detailed information is illustrated as follows.

In Table 1, it summarizes different research contexts that mentioned IB assistance operations. First, to plan a shipping route in ice, IB assistance is mentioned as a functional component to break the ice for merchant vessels. With the assistance operation, the path in ice could be optimized because of the shortened sailing distance in ice and the reduced fuel consumption (Lehtola et al., 2019; Zhang et al., 2017a, 2017b). Therefore, factors that are used to involve IB assistance in route

Table 1
Contexts mentioning IB assistance operation

No.	Context	The functionality of IB assistance	Reference examples
1	Route planning in ice	Keep ice channels open and traffic flow smooth	(Fedi et al., 2018, 2020; Lee et al., 2021; Valkonen and Riska, 2014; Wang et al., 2021; Dong et al., 2024)
2	Besetment evaluation	Breaking a ship loose	(Fu et al., 2016; Kubat et al., 2016; Turnbull et al., 2019; Vanhatalo et al., 2021; Xu et al., 2022)
3	Ship operability assessment in ice	Break the ice in front of merchant vessels	(Juva and Riska, 2002; Kuuliala et al., 2017; Li et al., 2021; Li and Huang, 2022; Milaković et al., 2019; Montewka et al., 2015, 2019; Xie et al., 2023)
4	Winter navigation system simulation	Keep ice channels open and traffic flow smooth	(Bergström and Kujala, 2020; Ding et al., 2016; Kondratenko et al., 2021; Kulkarni et al., 2022; Lindeberg et al., 2018)

planning can be potential factors that lead to IB assistance. Second, loosening a merchant vessel from ice is one of the main functions of IB assistance operations. Besetment occurrence reflects the need for IB assistance (Vanhatalo et al., 2021). Hence, factors leading to besetment can also trigger the need for IB assistance. Third, the context of ship operability in ice reflects how ice impacts ship performance. Involving IB assistance can affect ships' ice resistance and ice loads (Kuuliala et al., 2017; Milaković et al., 2019). Thus, factors that affect the ship's performance in ice can be potential factors that lead to the need for IB assistance. Finally, the IB workload assignment is of interest to simulate and optimize the winter navigation system (Kulkarni et al., 2022). Therefore, factors used to implement IB assistance for winter navigation simulation are the ones leading to the need for IB assistance.

Based on the contexts in Table 1, a literature search is conducted to collect potential factors affecting the need for IB assistance. To ensure an objective assessment of the scientific value of the literature, Web of Science and Scopus are used as the primary sources for reference searches, focusing only on English-written articles. Articles referring to the contexts mentioned above are deemed relevant for factor collection. The details can be referred to (Liu et al., 2023).

In Fig. 1 it lists the factors collected from references. There are 22 factors classified into four categories: ship-related category (SC), ice-related category (IC), weather-related category (WC), and human-related category (HC). As shown in Fig. 1, the ship-related category includes 5 factors. Firstly, ship ice class is the most frequently mentioned factor. Ice class refers to the ice-going capacity of a ship. According to the Finnish-Swedish Ice Class Rules (FSICR), there are five ice classes, 1 A SUPER (1 AS), 1 A, 1B, 1C, and II. 1 AS has the strongest ice-going capability, followed by 1 A. Ships with these two ice classes can be assisted without restrictions in severe ice conditions. While for 1B, 1C, and II, the availability of icebreaker assistance to Finnish and Swedish ports is restricted during peak winter due to their low ice-going capacity (BIM, 2020). Secondly, hull shape and ship type are potential factors as well. Hull shape matters for ice loads and ice resistance investigation, influencing the ice-going capability of the vessel (Kujala et al., 2018). Although the ship type consideration is limited to some specific types, this factor has been discussed by besetment evaluation and route planning studies (Fu et al., 2016; Kubat et al., 2012; Valdez Banda et al., 2015). Engine power comes as another potential factor. Engine power partly presents the ship's ice-going ability. Ships assisted by IB can reduce the power output when sailing in ice (Juva and Riska, 2002). To balance the navigation cost and efficiency, IB assistance service is an option for merchant vessels sailing in ice-covered waters (Kondratenko et al., 2021). Finally, ship length, width, and deadweight are collected as influencing factors because of their effect on the ice-going capabilities of the ship. Furthermore, authorities set restrictions on ship deadweight to determine whether a vessel is entitled to be assisted by IB (Matala and Suominen, 2022).

The ice-related category covers 9 factors. Ice concentration and ice thickness are the 2 most frequently mentioned elements. Ice concentration generally represents a fraction of a measured area covered by ice. Ice can be categorized into diverse groups (e.g., new ice, grey ice, etc.) according to thickness (Milaković et al., 2019). The ice condition with high concentration and thickness would increase the navigation difficulty of merchant vessels, leading to a high probability of needing IB assistance. Rather than express ice appearance in general, ice types are presented by level ice, ridged ice, and rafted ice. Rafted and ridged ice can be deformed from level ice (Haapala et al., 2005), while ridged ice is significantly thicker than other ice types, leading to harsh conditions where IB assistance would be needed (Kubat et al., 2014).

Apart from the concentration and thickness of different ice types, some other ice characteristics have been discussed by existing studies, such as ice floe size, dynamic ice, brash ice, and ice compression. Ice floe is a piece of ice floating on the sea surface, impacting ice loads on ship hulls (Huang et al., 2021). Goncharov et al. (2023) indicated that broken ice floes in channel brings danger for merchant vessels, as they would make the rotation of ship propeller difficult, reduce ship thrust, and affect ice resistance. Brash ice occurs when ice floes or level ice breaks up into smaller floating chunks. Ship resistance would be affected by such ice conditions, leading to speed changes (Guo et al., 2018). If a ship is not able to move in such a condition, IB assistance operation is an alternative. Dynamic ice can be generated by wind, wave, and current forces (Lensu and Goerlandt, 2019). Zhang et al. (2023) proposed a novel artificial potential field-based model to investigate the sea ice risk considering ice drift, which can be used to present the probability of a ship stuck in ice during convoy operation. Usually, dynamic ice moving perpendicular to the midship section is considered hazardous, with a high risk of getting stuck, indicating that IB assistance would be needed (Lu et al., 2021). It is assessed to investigate ship performance in ice or predict besetting probability (Pärn et al., 2007). Ice compression is

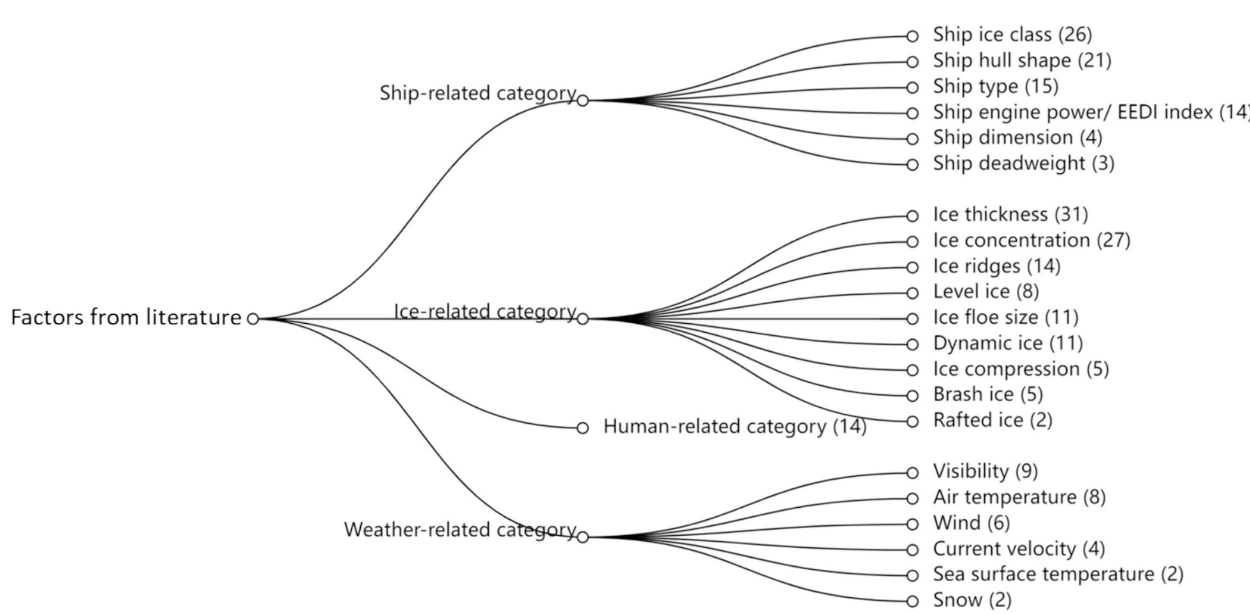

Fig. 1. Collected Factors that may affect the navigation mode determination (the number in the parenthesis indicates the response number).

another factor mentioned by references (Kubat et al., 2012; Pärn et al., 2007). Although its definition is still imprecise, ice ridges and wind have been identified as the main forces leading to ice compression (Kubat et al., 2012; Wang et al., 2021).

For the weather-related category, 6 factors are collected from the literature, including visibility, air and sea surface temperature, wind, snow thickness, and current. Weather factors are often discussed by besetment evaluation using the Bayesian networks; see examples (Fu et al., 2016; Montewka et al., 2015; Xu et al., 2022). The wind has been discussed by the research investigating ship performance in ice, as it is one of the driving forces of ice movement and ice compression (Kubat et al., 2014; Lensu et al., 2013). Human factors are often mentioned in studies on risk analysis. For example, lacking navigational experience would lead to risky conditions (e.g., besetment events) (Xu et al., 2022).

However, among the factors listed in Fig. 1, most of the factors have not been used for directly analyzing the need for IB assistance. Currently, no study systematically investigates the effect of these factors to better understand the need for IB assistance. Only a limited number of factors have been used to indicate the need for IB assistance in existing references, see Table 2.

In Table 2, it illustrates two sets of factors that are currently used to estimate the need for IB assistance. The first set (Set I) consists of factors considered by the Polar Operational Limit Assessment Risk Index System (POLARIS) and Arctic Ice Regime Shipping System (AIRSS) (Fedi et al., 2018, 2020; Lee et al., 2021). POLARIS and AIRSS are systems that can be used to evaluate navigational risk. The systems consider ship ice class, ice concentration, and the range of ice thickness to calculate the navigation risk index. If the index is lower than 0, it indicates IB assistance would be a navigational option to secure navigation safety. The second set (Set II) comprises factors that are taken into account in winter navigation simulation studies. Ship speed is calculated as a function of operational conditions, such as equivalent ice thickness with an assumption of engine power (Kulkarni et al., 2022; Martin et al., 2016; Tarovik et al., 2017). Ship speed is set as a sole threshold to determine the need for assistance. If the speed is below the threshold (e.g., 3 knots), the ship needs to wait for IB assistance. Otherwise, the ship can proceed with independent navigation in ice.

The research gap can be observed from the literature review when comparing the factors in Fig. 1 to the ones in Table 2. The effect of operational conditions on the need for IB assistance has not been thoroughly examined. Multiple factors, including ice conditions, weather, and ship specifications, could influence the estimation of the need for IB assistance. The limited number of factors shown in Table 2 does not fully account for complex winter navigation scenarios. Therefore, under the guidance of Fig. 1, it is necessary to conduct a data-driven study to identify and quantitatively analyze a comprehensive list of factors impacting navigation mode estimation.

3. Methods

The paper proposes a data-driven framework for identifying influencing factors and quantifying their effect on the need for IB assistance.

Table 2
Factors assessed to determine the need for IB assistance

No	The name of the factor considered by the reference				Reference examples
	IC	*IT*	*SIC*	*SP*	
Set I	✓	✓	✓		(Fedi et al., 2018, 2020; Lee et al., 2021)
Set II				✓	(Bergström and Kujala, 2020; Kulkarni et al., 2022; Lindeberg et al., 2018; Tarovik et al., 2017)

Note *IC*: ice concentration; *IT*: ice thickness; *SIC*: ship ice class; *SP*: ship speed.

The framework includes three stages, as shown in Fig. 2. A brief introduction of the framework is described below, and more details are provided in Sections 3.1–3.3.

Stage I focuses on multi-sources data collection and integration. By integrating multiple data sources (traffic, environment, and ship specifications information), factors to be assessed can be presented quantitatively. This step provides data sources for the following stages. Under stage II, data points are labeled by a multi-step clustering method to distinguish instances of assistance operation and independent navigation. This is followed by data selection, filtering, and balancing. The outcome of stage II is subsequently used to analyze the influencing factors in the following stage. Finally, in Stage III, influencing factors analysis is done using logistic regression, and the effectiveness of the identified factors regarding modes classification capability is measured at the end. The following subsections describe these three stages in more detail.

3.1. Stage I: multi sources data collection and integration

To gather data about the factors in Fig. 1, data sources that can provide information regarding traffic information, environmental conditions, and ship specifications, are needed. Data from three different sources – automatic identification system (AIS), Helsinki Multi-category sea-ice model (HELMI), and the operational management system of winter shipping (IBNet), are integrated in this paper to represent the operational conditions.

The first source is maritime traffic data, represented by AIS data provided by the Finnish Transport Infrastructure Agency. It is used to present traffic scenarios. The detailed description of the data source can be found in Liu et al. (2022). Dynamic ship positions and marine mobile service identity (MMSI) are extracted from AIS. Although the quality of AIS data was initially mediocre in the early implementation years due to the error information related to speed, course, and location, there has been a significant improvement in the quality of AIS data over the past decade (Goerlandt et al., 2017). In the current paper, we implemented the error filtering method used by Liu et al. (2020) to eliminate error information related to speed, course, and geographical coordinates and exclude trips of insufficient duration that do not encompass valuable traffic information.

The second data source comes from the Helsinki Multi-category sea-ice model (HELMI) which is developed for climate applications. The model has been used as a basis for describing the sea ice conditions (Montewka et al., 2015; Goerlandt et al., 2017). Details of the model can be found in Haapala et al. (2005). Lensu et al. (2013) indicated that the HELMI model has been developed and compared with observed data in many projects during 10 years. The comparison with ice charts has shown that the model serves its purposes. The data for both ice factors (IF) in the ice-related category and weather factors (WF) in the weather-related category in Fig. 1 are collected from the HELMI model. The HELMI stores factors in a three-dimensional NetCDF format, where variables vary with time over the fixed grid cell. The grid has 556 nodes in the latitude direction and 415 nodes in the longitude direction, with each grid cell covering an area of 1 square nautical mile (nm) and an hour temporal resolution. Each node has all variables, and each variable has its own value that is updated hourly.

Among the 6 weather factors in Fig. 1, wind speed, snow thickness, and air temperature can be obtained from the HELMI model. It is worth noting that the snow thickness in HELMI is the average thickness per unit area over the level ice cover (Rontu et al., 2019). The detailed information refers to Haapala et al. (2005) and Rontu et al. (2019). Although visibility and currents have been cited by references, data on these two factors are currently not available. Sea surface temperature value is constant in HELMI during the study period and hence does not add value to the impact analysis. Thus, this factor is not included in the following stage as well.

As mentioned above, HELMI provides ice factors. The concentration

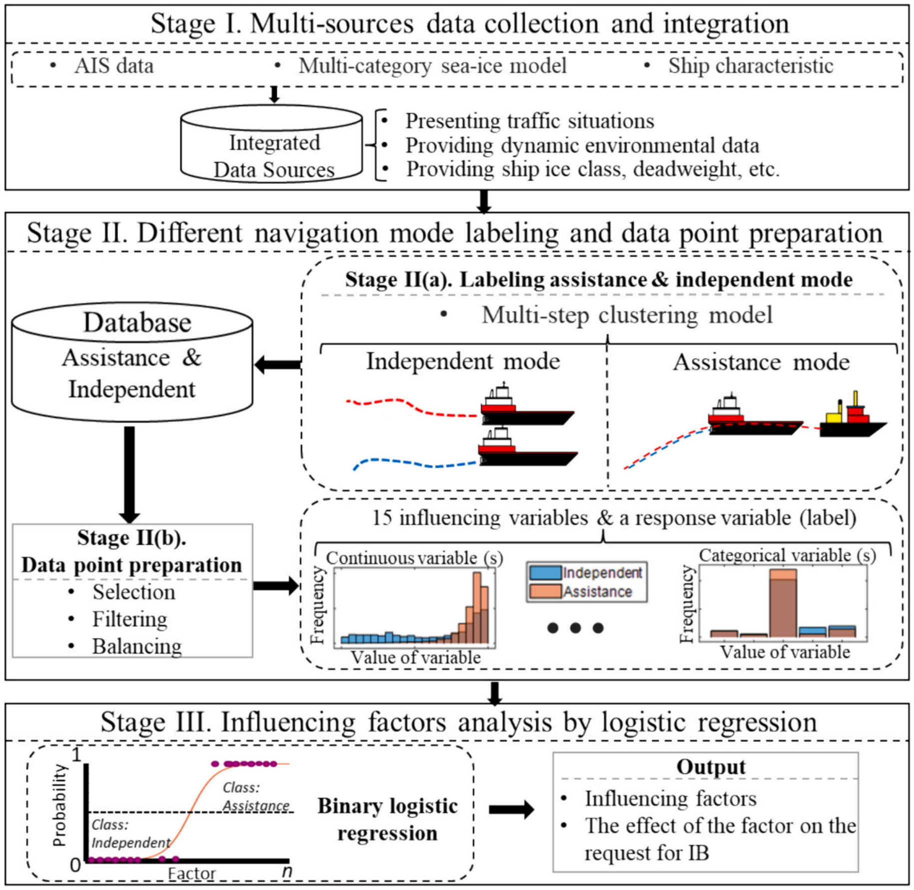

Fig. 2. Framework for influencing factors analysis.

and thickness of level, ridged, and rafted ice are recored in the model, covering 5 of 8 ice factors shown in Fig. 1. There are 7 categories, 5 level ice categories, ridged ice category, and rafted ice category. Each category represents an average ice thickness per unit area (1 square nm). The level ice concertation is derived by summing the values from all five categories. The concentration of ridged and rafted ice are directly provided by the model record. The thickness of level ice, ridged ice, and rafted ice is calculated by dividing the average thickness obtained from HELMI by their respective concentrations. However, getting information on ice floe size, dynamic ice, brash ice, and ice compression from HELMI is not feasible. To our knowledge, currently, there is a lack of data sources that can accurately capture the conditions of dynamic ice, compressed ice, brash ice, and ice floes in the Baltic Sea. While the information on these ice conditions is usually collected by observations, obtaining observed ice information for tens of thousands of trips with these ice conditions poses a significant challenge. However, ice speed exhibits a strong correlation with wind speed, and ice compression is primarily driven by the combined forces of wind and ice ridges (Pärn et al., 2007). Thus, the inclusion of the wind speed partially mediates the issue of not having direct data on ice compression and dynamic ice.

Information from IBNet is the third data source. IBNet is an IT-based online system jointly operated and maintained by the Finnish Transport Infrastructure Agency and the Swedish Maritime Administration to coordinate icebreaking operations (BIM, 2020). IBNet is used in this paper to collect data on ship factors (SF) in the ship category in Fig. 1. From IBNet, ship length, width, type, deadweight, engine power, and ice class are obtained. Although ship hull is vital for ship performance investigation in ice, data on ship hull information, like the angle of the bow, is not available. Furthermore, hull information varies from ship to ship, which is impossible to get for all vessels visiting the Baltic Sea during the study period. Hence, the ship hull is excluded in the following analysis and discussion.

Table 3
Factors presented by data for quantitative analysis

No	Factors from the integrated dataset	No	Factors from the integrated dataset
IF 1	Level ice concentration (in tenths)	WF 3	Wind speed (m/s)
IF 2	Ridged ice concentration (in tenths)	SF 1	Ship length (m)
IF 3	Rafted ice concentration (in tenths)	SF 2	Ship width (m)
IF 4	Thickness of level ice (m)	SF 3	Ship engine power (Kw)
IF 5	Thickness of ridged ice (m)	SF 4	Ship deadweight (T)
IF 6	Thickness of rafte d ice (m)	SF 5	Ship ice class
WF 1	Snow thickness (m)	SF 6	Ship type
WF 2	Air temperature (°C)		

The factors for which data can be collected are summarized in Table 3, based on the presentation in Fig. 1. While the human factor is observed as an influencing factor, it is impossible to collect data about human decisions and reasoning on board when IB assistance happened for tens of thousands of trips. The navigational patterns resulting from human made decisions can be mirrored in the observed trips (independent navigation and IB assistance operation) presented by the dataset. The approach of this paper is to quantitatively understand the influencing factors behind the actual cases based on the available data.

Data collected from three different sources need to be integrated before use. Ship factors are combined with dynamic ship traffic information using MMSI. Dynamic ship position extracted from AIS data is integrated with the corresponding ice and weather factors. To integrate ice and weather data with AIS messages, we employed the method outlined in Lensu and Goerlandt (2019). Given that ice and weather conditions typically do not undergo significant changes within a short time frame (within an hour), it is reasonable to use the values from the nearest temporal and spatial point. For example, as shown in Fig. 3, the red-highlighted cross mark represents an AIS message with a timestamp (occurred at 15:50) and location information (indicated by latitude and longitude). To obtain the corresponding values from the HELMI model, we identified the index of the nearest timestamp (which occurred at 16:00) and nearest location (the point a as shown in Fig. 3). The values corresponding to this index in the attribute dataset are then extracted and utilized as matches. According to the statement in Lensu and Goerlandt (2019), the location accuracy of this match is about the size of one grid cell or even better.

3.2. Stage II: different navigation mode labeling and data points preparation

Stage II (a). Different navigation mode labeling: After the multi-sources data integration, each data point consists of 15 factors shown in Table 3, reflecting traffic conditions, ice conditions, and weather conditions. However, initially, the data points are not inherently categorized as either assistance or independent cases, necessitating the need for labeling to be conducted. The process of labeling navigation mode is to identify the navigation mode from the dataset and assign the label that specifies if the data point represents an assistance or independent navigation case. Our previous study (Liu et al., 2022) adopted a multi-step clustering method to label navigation mode and validated the outcomes using real-life IBNet assistance records.

Stage II (b). Data points preparations: The number of independent cases is much greater than that of assistance cases in the Baltic Sea. To ensure data consistency and comparability, three constraints are used for independent case selection. First, to be qualified for IB assistance service, a minimum deadweight and ice class are mandatory for merchant vessels (FSICR, 2021). Given this constraint, only merchant vessels larger than 1300 DWT and ice class higher than II are considered for the study period (SMHI, 2023). Second, 98% of assistance cases in the study period happened at 63° N and above. Thus, 63° N and above is used to select data points of independent cases. Finally, among different ship types, the assistance instances contain bulk, container ship, general cargo, RoRo cargo, and tankers. Therefore, the above five types are also used to filter independent cases.

To ensure the integrity and validity of the established dataset, data cleaning is further conducted by checking each data point in the database. Missing information, such as missing ship deadweight, unavailable ice factor at a specific position, and obvious outliers are detected and removed from the dataset. To detect outliers, interquartile range (IQR) is applied, see Table 4 (Tukey, 1977).

Table 4
Interquartile range method for outlier detection

Input:
$D = \{d_1, d_2 \ldots, d_n\}$ is a column of data points **Output:** Outliers **Process:** 1. Calculation of Quartiles: $Q1, Q3 = s.quantile(.25), s.quantile(.75)$ 2. Interquartile Range (IQR): $IQR = Q3 - Q1$ 3. Bounds for Outliers: $Low, Up = Q1 - 3{*}IQR, Q3 + 3{*}IQR$ 4. Identifying Outliers: Outliers are those values in series s where: $Outlier = \{d \in s \mid x < Low, or\ x > Up\}$

Finally, random under-sampling is employed for independent cases to avoid a skewed class proportion (independent case vs. assistance operation). This method is chosen when there is plenty of data for an accurate analysis (Brownlee, 2020). The aim is to reduce the number of data points by removing samples from independent cases, with the goal of achieving an equal number of samples for both operational modes. When there is a significant disparity in sample sizes between two classes, capturing the characteristics of the minority class becomes challenging. The method can be represented as follows: $N_{majority}$ is the number of instances in the majority class; $N_{minority}$ is the number of instances in the minority class. To achieve a 1:1 ratio between the majority and minority class, $N_{new\ majority} = N_{minority}$, $N_{remove} = N_{majority} - N_{new\ majority}$ is the number of instances that need to be randomly removed from the majority class. After this step, the database has a balanced representation of two operations.

3.3. Stage III: influencing factor analysis by logistic regression

Binary logistic regression is a statistical model that estimates the probability associated with one of the two classes in the dataset (Gambella et al., 2021). It can take both continuous and discrete variables as inputs. The result of the model is the impact of each input variable on the target event of interest. There are two main steps involved.

- Step 1. Multicollinearity detection and explanatory variables selection

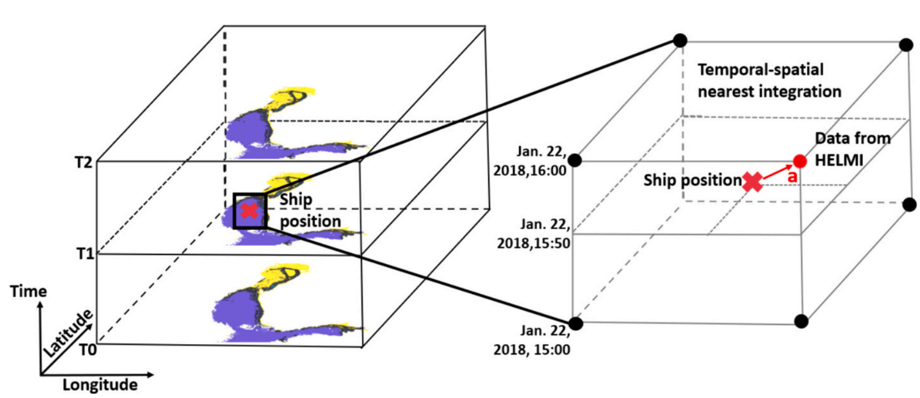

Fig. 3. An example of matching AIS data with data in NetCFD format.

In logistic regression, no assumptions are made on the distribution of any explanatory variables. However, the multicollinearity of two or more independent variables would affect the performance of coefficient estimation (Bewick et al., 2005). Given a little change in the data, multicollinearity can cause unstable explanations of strongly correlated input variables. It is generally acceptable to have moderately correlated variables, but high levels of multicollinearity can be problematic and should be a cause for concern. The variance inflation factor (*VIF*) is adopted to detect multicollinearity among factors (Daoud, 2017). It technically measures how much the squared standard deviation of an estimated regression coefficient is increased because of collinearity. It can be measured for each explanatory variable by Eq. (1). To interpret the meaning of *VIF*, Table 5 is used. It is advisable to remove or appropriately combine variables with a variance inflation factor (*VIF*) higher than 5. The process of the factor determination can be found in Appendix A.2.

$$VIF = \frac{1}{1 - R_i^2} \tag{1}$$

Where R_i^2represents the unadjusted coefficient of determination for regressing the i^{th} explanatory variable on the remaining ones.

- Step 2. Logistic regression analysis

A logistic regression models the chance of the target event based on individual variables. Given a chance is a ratio, the logarithm of the chance is modeled by Eq. (2). The process of the regression coefficient determination can be found in Appendix A.1.

$$log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_m x_m \tag{2}$$

Where p is the chance of the occurrence of an event (e.g., assistance operation in the current paper), $\frac{p}{1-p}$ is the odds of the events, β_0 is the intercept term of the model, and $\beta_1 \ldots \beta_m$ present the regression coefficients associated with the target event and x presents the input variable.

The regression coefficient can explain a brief relationship between a variable and the target event. Given the association is significant at the 0.05 level (2-tailed), if the coefficient is larger than 0, it indicates that they are positively correlated, and vice versa. However, coefficients cannot measure the exact effect of a variable on the target event. To represent the effect extent of the variable, the odds ratio (*OR*) value is adopted (Sperandei, 2014). *Odds* is explained as the ratio of the target event happening to the event not happening. *OR* is explained as the ratio of odds, which is a statistic that quantifies the strength of the association between the explanatory variable and the target event. Important points on interpreting *OR* in logistic regression are briefly described below. Further details can be found in (Lavalley, 2008; Sperandei, 2014).

- Assuming X is a variable of a multivariant logistic regression model, if X is a continuous variable, the logarithm of the odds of the event changes with a 1-unit change in the X, keeping other variables unchanged. If X is a categorical variable, the logarithm of the odds of the event changes with the change of the dummy variable over the reference group, keeping other variables unchanged.

Table 5
VIF interpretation (Daoud, 2017)

VIF value	Interpretation
$VIF = 1$	Not correlated
$1 < VIF < 5$	Moderately correlated
$5 \le VIF$	Highly correlated

- 100 times the *OR* minus 1 (e.g., $100^*(OR - 1)$), gives the percent change in the odds of the event corresponding to a 1-unit increase in X.
- If *OR* value is higher than 1, it indicates that the odds of the event increase with the change of X, and vice versa.

For this paper, the binary logistic regression models the need for IB assistance as a function of factors listed in Table 3. This can be considered as a classification problem where all factors in Table 3 are input variables for the model, and the navigation mode (independent case vs assistance case) is the response variable. The results are presented in the following section.

4. Results

In this section, a database consisting of scenarios of independent and assistance operations was established, and influencing factors were analyzed by logistic regression.

4.1. Result of the database of assistance and independent navigations

According to the method demonstrated in Stage I, this study integrated three different data sources to present traffic and operational conditions. The data sources cover mild-winter months from January to February in 2018. In Fig. 4, it shows examples of integrated traffic and ice scenarios. Each point represented by the spatial matrix was matched with its corresponding operational conditions.

In Fig. 5, itshows all 15 factors presented in Table 3. All experiments were running on a computer with Intel i7-12700H CPU, 32 GB of RAM and NVIDIA RTX A2000 GPU. According to Stage II in Section 3.2, data preparation was conducted. There were 559,694 data points classified into two navigation modes (independent navigation or assistance operation) (Liu et al., 2022), and 558,482 were left after the missing information removal, including 83,901 assistance operation and 474,581 independent navigation data points. Next, we removed the duplications, leaving 80,566 data points in the dataset based on the 15 factors. Data cleaning was then conducted to remove obvious outliers using IQR method described in Section 3.2. After the data cleaning, 6357 assistance cases and 60,628 independent cases were reserved. Then, the number of independent points were under-sampled to match the number of assisted points. The random under-sampling method provided by the imbalanced-learn Python library was used to balance the data points of different navigation modes. The final dataset consists of 12,714 data points presenting two navigation modes equally.

4.2. Result of factors effect analysis

4.2.1. Factor effect analysis based on the entire database

According to Stage III in Section 3.3, the effect of factors is evaluated by logistic regression. According to Eq. (1), *VIF* of each variable is calculated. The result is shown in Fig. 7 (a). It is observed that the factors, including ship length, width, deadweight, and power, have *VIF* larger than 5, indicating that these 4 variables could be highly correlated with each other. The pairwise correlation matrix is used to investigate how correlated these variables are. In Fig. 6, it shows that these four variables are correlated, and coefficient values vary from 0.719 to 0.923. The correlations are practically reasonable as they are static specifications of a vessel. The longer the length, the wider the width, and vice versa. The larger the ship dimension, the higher the deadweight and engine power. Correlated factors need to be combined reasonably or partly removed to eliminate the effect of multicollinearity on logistic regression. In this case, among these four factors, one factor is selected to be the input, and the remaining ones are reserved for robustness check.

In Fig. 7(b), it shows the result of the updated list of variables. *VIF* of the selected variables are all <5, indicating there is no strong multicollinearity existing.

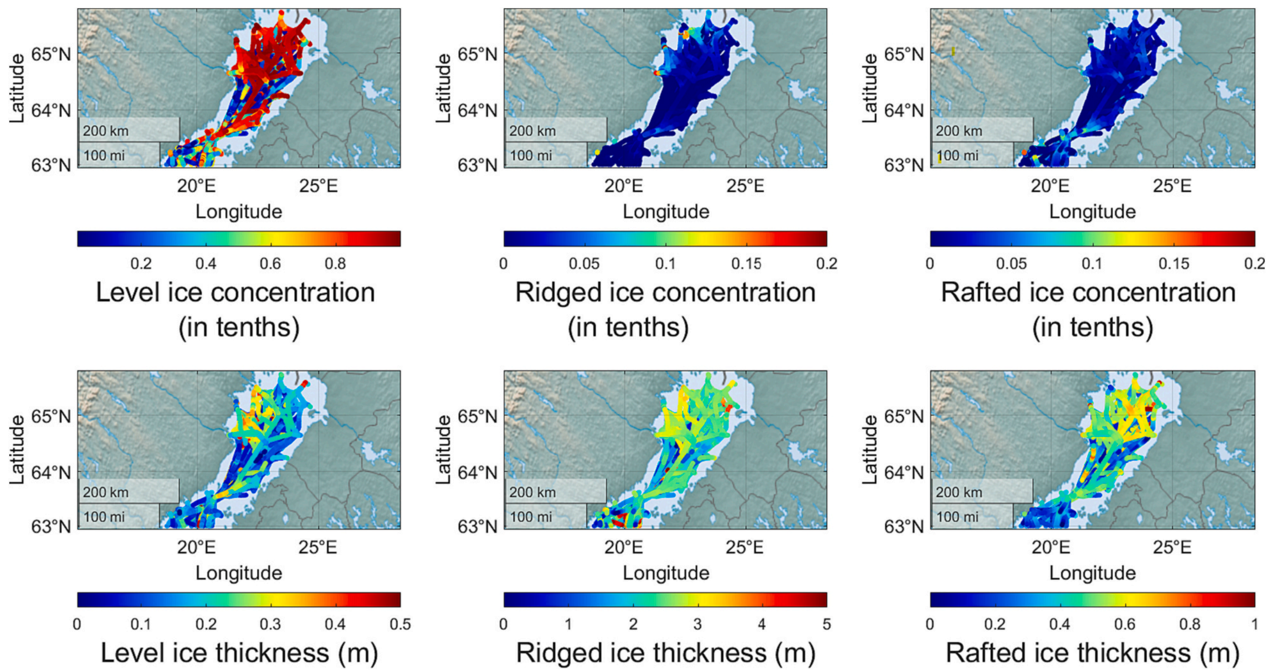

Fig. 4. Integrated traffic and ice scenarios in the Northern Baltic Sea.

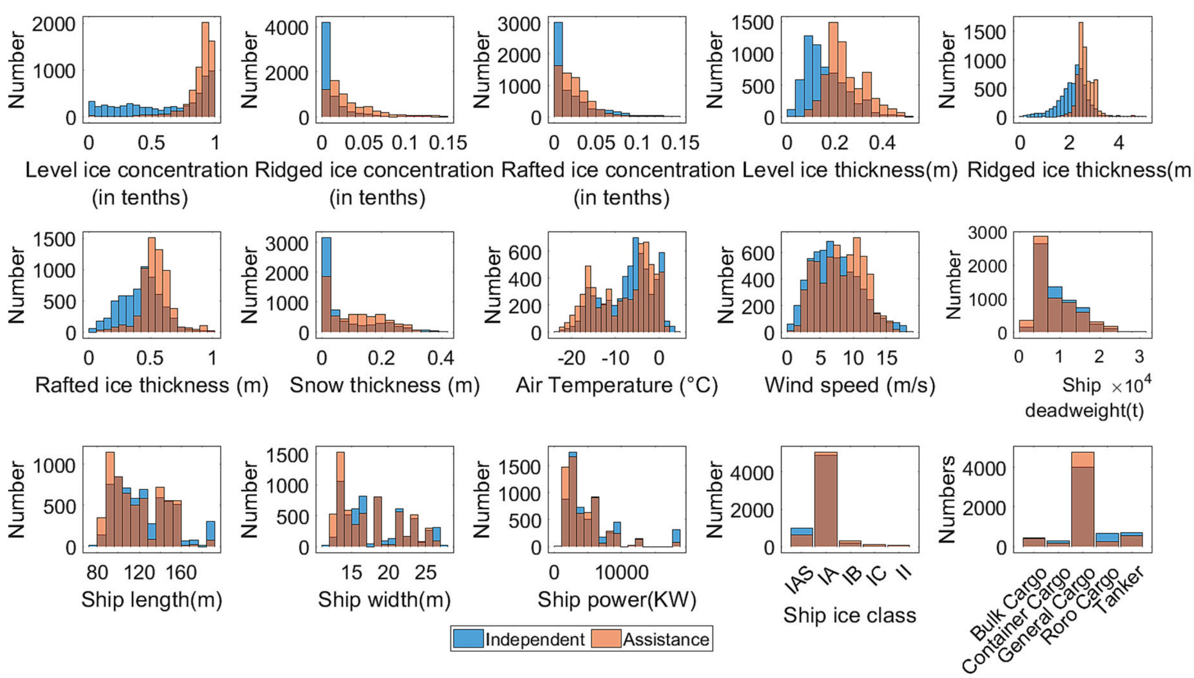

Fig. 5. Statistics of the database of assistance and independent operations.

After the factor selection, logistic regression is implemented according to the process of statistical analysis as shown in Section 3.3. In Table 6, it shows the logistic regression summary, including the coefficient, *OR* value, the range of *OR* value, and the corresponding confidence level. In Fig. 8, it shows the result of the robustness check when changing ship characteristic representatives.

In Table 6, it can be observed that different types of variables have diverse impacts. In general, ice factors have a more significant effect compared to ship factors and weather factors. Ridged ice concentration has the most significant impact on the target event, followed by level ice concentration. The interpretation of the identified influencing factors is explained in depth in the following section.

Before the in-depth discussion on distinct factor effects, factor impact robustness is assessed, as shown in Fig. 8. To check the robustness when changing the representative variable of ship dimension, ship deadweight is replaced by ship length, width, and power, respectively. Air temperature is not statistically significant at the 0.05 level, it is removed in the robustness check part. It is evident that when changing representative

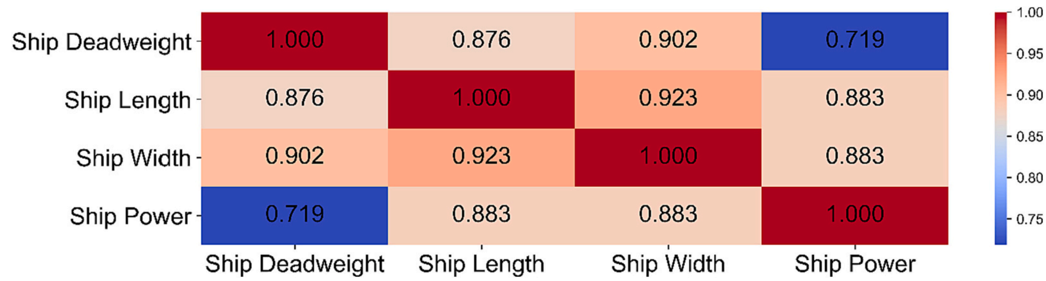

Fig. 6. Correlation matrix of variables with high *VIF*.

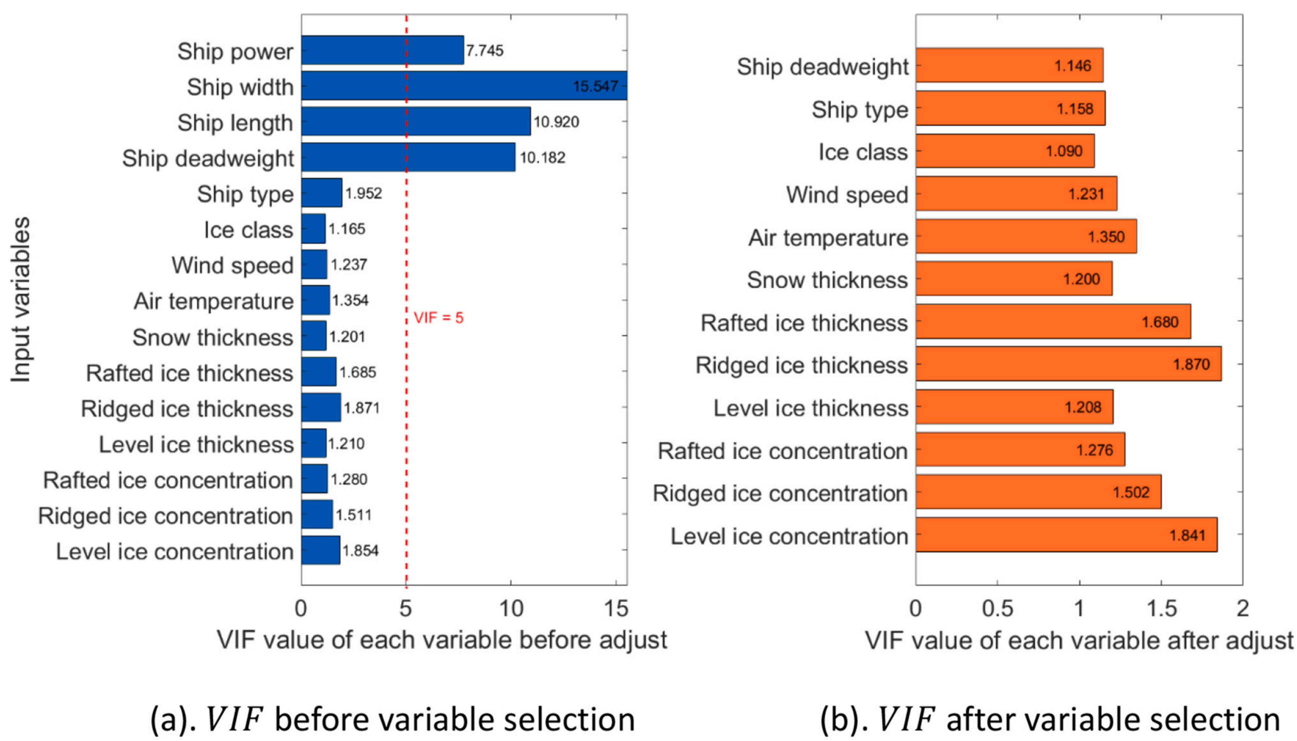

Fig. 7. (a). *VIF* before variable selection Fig. 7 (b). *VIF* after variable selection

ship dimension, the effect level remains stable regarding *OR* values of factors. We can conclude that the association result is robust against the representative ship characteristic variable change when determining the need for IB assistance. Thus, the final list of identified influencing factors is shown in Fig. 9.

The detailed interpretations of influencing factors are explained as follows:

Influencing ice factors: Based on the effect analysis results of logistic regression (Table 6 and Fig. 8), among all the ice variables, ridged ice, and level ice concentration have the most significant impact, followed by ridged ice thickness, level ice thickness, rafted ice thickness, and rafted ice concentration. To interpret the effect result, we use ridged ice concentration as an example. Assuming all other variables are held constant, the estimated coefficient for ridged ice concentration suggests a positive correlation with the need for IB assistance. The *OR* value quantifies this relationship, indicating the multiplicative increase in the odds of requiring IB assistance for every one-unit increase in ridged ice concentration. Furthermore, this association result is statistically significant at the 0.01 level. The higher the *OR* is, the more significant the effect of the variable.

These findings can be supported by the previous study (Chang et al., 2015; Huang et al., 2021; Montewka et al., 2014). Ice ridges have a significant effect on navigation safety. One potential reason could be that ridged ice is generally thicker than level and rafted ice, increasing the ice resistance and threatening the ship hull. It is known as well that if there is wind forcing on ridges, more challenging ice condition would appear as ice compression can be generated, leading to a high probability of getting stuck or a high risk of getting hull damage, especially for ships with low ice-going capability (Kuuliala et al., 2017). However, it is observed that ridged ice concentration has a more significant impact compared to its thickness. This observation is interesting, as it delivers the information that the high concentration would alert the ships to be aware of the harsh ice conditions. IB assistance has priority as long as the navigating area is covered by ice with high concentration.

It is noticeable that *OR* value of the concentration of rafted ice is <1, presenting a relatively minor effect compared to the concentration of ridges and level ice. Rafted ice concentration is negatively correlated with the target event, indicating that the increase of this factor did not increase the odds of the need for IB assistance. This is because the effects of factors are coupled, and the impact of rafted ice concentration is weakened by ridges and level ice. According to the database statistic in Fig. 5, the level ice concentration is significantly higher than that of

Table 6
Logistic regression summary

No.	Variable	Coefficient	OR	Lower 95% CI	Upper 95% CI
1	Level ice concentration	0.826	2.283**	2.121	2.458
2	Ridged ice concentration	1.017	2.766**	2.537	3.016
2	Rafted ice concentration	−0.383	0.682**	0.636	0.731
3	Level ice thickness	0.486	1.626**	1.498	1.764
4	Ridged ice thickness	0.547	1.727**	1.597	1.868
5	Rafted ice thickness	0.232	1.261**	1.156	1.376
6	Snow thickness	0.062	1.064*	1.010	1.120
7	Air temperature	0.034	1.035	0.982	1.091
8	Wind speed	0.471	1.602**	1.518	1.691
9	Ship dimension[1], *	−0.061	0.941	0.866	1.022
Ice class (Reference: II) **					
10	1AS	−1.618	0.198**	0.122	0.321
11	1A	−1.392	0. 249**	0.153	0.404
12	1B	−1.518	0.219**	0.127	0.379
13	1C	−0.714	0.490*	0.255	0.939
Ship Type (Reference: Tanker) **					
14	General Cargo	0.338	1.403**	1.179	1.667
15	Container ship	−0.318	0.727*	0.546	0.970
16	RoRo Cargo	−0.659	0.517*	0.396	0.676
17	Bulk Cargo	0.014	1.014	0.809	1.270

Note 1: In this table,ship deadweight presents ship dimension.
(**): The association is significant at the 0.05 level (2-tailed).
(*): The association is significant at the 0.01 level (2-tailed).

rafted ice. Furthermore, although the distrubition of rafted ice concentration is similar to that of ridged ice in Fig. 5, ridged ice is much thicker than rafted ice, which lead to harsher ice conditions where IB assistance is highly likely needed.

Influencing weather factors: The wind is recognized as one of the main factors influencing navigation mode determination. The *OR* value of wind indicates that the increase in wind speed would increase the probability of the need for IB assistance. The result is in line with the findings from previous studies (Abbassi et al., 2017). In the Baltic Sea, the wind is one of the main causes of ice drift and ice pressure, leading to ridges, rafting, and slush barriers in Baltic Sea (Kubat et al., 2016). This harsh ice condition requires IB to assist merchant vessels in navigating to reduce the potential risk (Berglund et al., 2007). The observed snow thickness and air temperature have a slightly positive impact. However, the value for air temperature is not significant between assistance and independent mode at the 0.05 level. Thus, the effect of this variable is considered insignificant.

Influencing ship factors: The effect of ship factors is assessed from three aspects, namely, ship dimension presented by ship deadweight/ dimension/engine power, ship ice class, and ship type. These three factors are all associated with the need for IB assistance. Ship ice class and ship type are categorical and are modeled as dummy variables. II ice class is used as the reference category for ship ice class. Compared to II, the remaining ice classes of 1 AS, 1 A, 1B, and 1C have a lower impact. Overall, given the ice class rules in the Baltic Sea can be satisfied, II has the most apparent effect on the need for IB assistance among all ice classes, followed by 1C. Although ships with high ice classes, such as 1 AS and 1 A, are the common ships being assisted by IB, they have a lower impact on the need for IB assistance than II and 1C in similar ice conditions. The findings on the effect of ice class are aligned with the previous studies and empirical knowledge. Ice class rules are assigned based on the ice-going capability of a merchant vessel, resulting in the varying odds of IB assistance need for different ice classes (FTIA, 2021). To ensure a safe navigation procedure of a merchant vessel, the lower the ice class, the higher probability of being assisted by IB.

For ship type, the tanker is used as the reference category. Compared to tankers, general cargo has a more significant effect. Container and RoRo ships have a lower impact on the need for IB assistance. The explanation is that the ice class range of general cargos entering the Baltic Sea is wider, varying from II to 1 AS. Low ice class leads to the necessity of the need for IB assistance. RoRo ships, in general, have high engine power requirements because of their high open water speed. They may need less IB assistance in reality (Riska et al., 1997). On the other hand, Fig. 5 shows general cargo presents the most significant percentage of traffic volume. Based on winter traffic statistics in Finnish and Swedish maritime areas, general cargo consists of 30% of the total traffic reported during a winter month, followed by tanker with 25% of the reported traffic. The influence of general cargo and tanker might be associated with the traffic volume. This observation aligns with the previous finding in Valdez Banda et al. (2015). However, the result of bulk cargo was not statistically significant at the 0.05 level. It indicates that this ship type does not significantly impact the need for IB assistance probability.

For ship dimension, it is presented by ship deadweight, length, width, and power individually (see Fig. 8). *OR* value of this factor is in a stable range varying from 0.824 to 0.941. This indicates that the smaller vessel has a higher probability of triggering the need for IB assistance. This finding is evidenced by the study of Valdez Banda et al. (2016), which found that the smaller the ship is, the higher the risky situations (e.g., getting stuck in ice) in ice-covered waters would be.

In Fig. 9, it summarizes the findings on influencing factors based on the logistic regression analysis, which is presented by the average value from robustness check result. To obtain insights on the extent to which the identified factors can improve the navigation modes classification, a classification performance comparison is implemented by using factors in Fig. 9 and currently used factors shown in Table 2. The details are

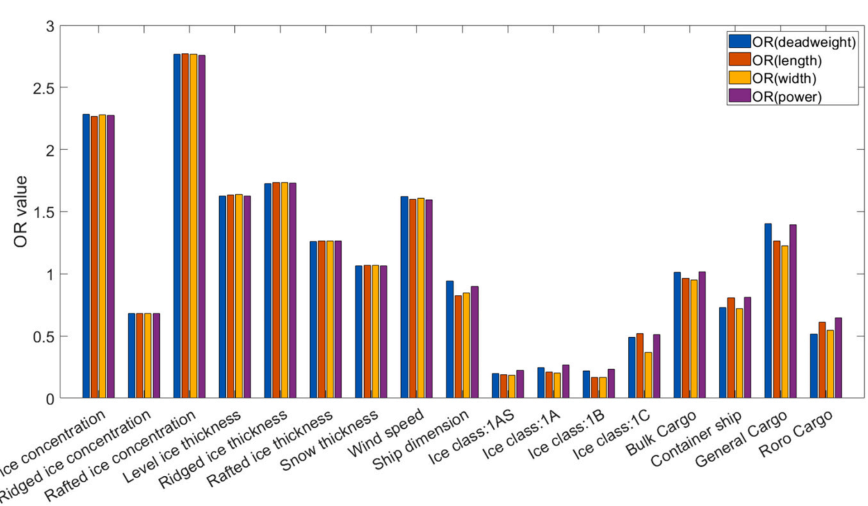

Fig. 8. Robustness check of association results under alternative ship dimension

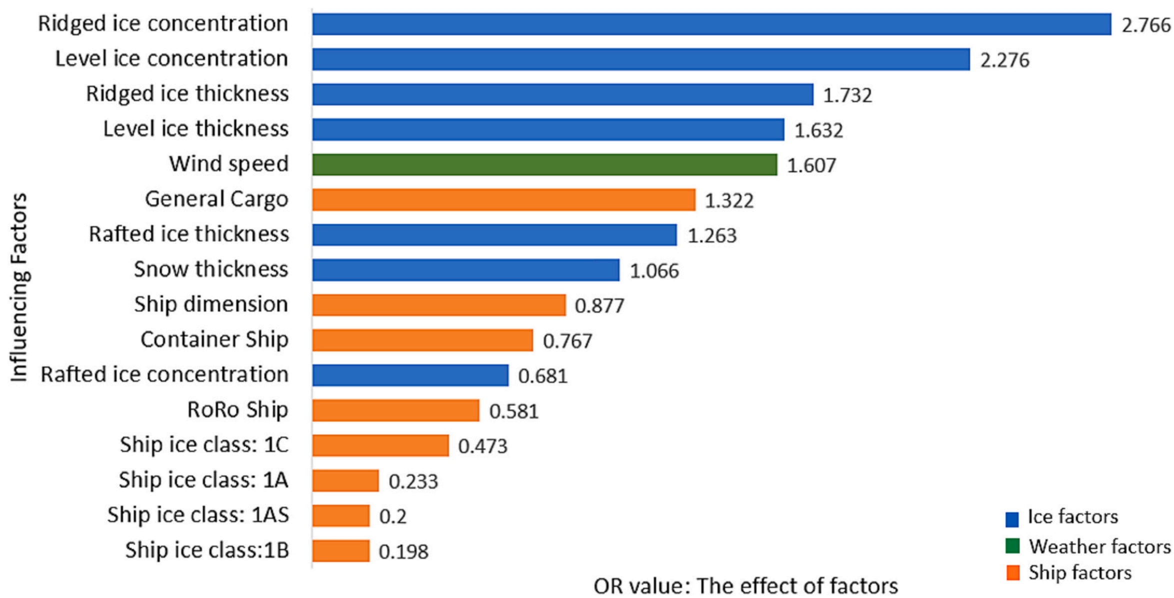

Fig. 9. Identified factors that lead to the need for IB assistance

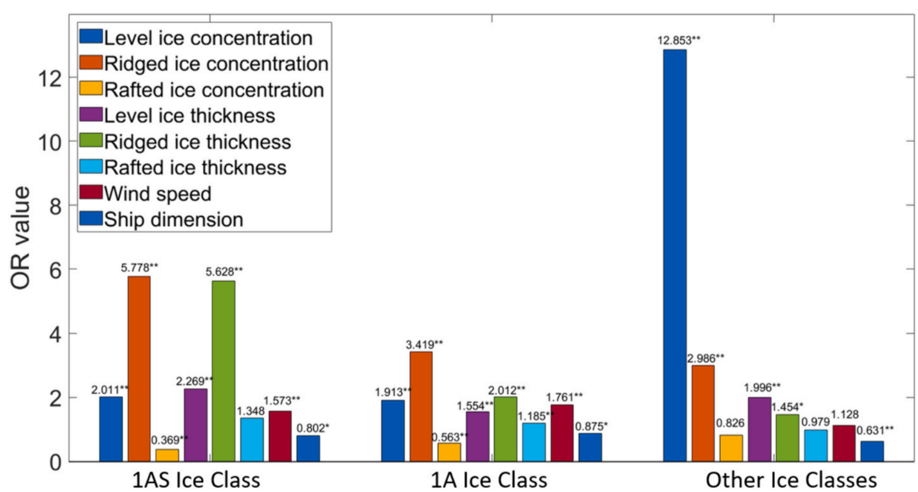

Fig. 10. *OR* values of influencing factors for different ice classes (Note: (**) indicates the association is significant at the 0.05 level (2-tailed); (*) indicates the association is significant at the 0.01 level (2-tailed)).

illustrated in Section 4.3.

4.2.2. *Factor effect analysis with the fixed ship ice class*

Based on the entire dataset shown in Fig. 5, the 1A ice class presents skewed traffic statistics. This means that the 1A ice class might dominate the factor effect analysis. Thus, an investigation of the factor effect under the control of ship ice class is conducted. It is notable that based on the available data in the current paper, when ship ice class is fixed, ship type diversity within one ice class group is restricted as well, leading to poor statistical power. Thus, ship type is excluded from the discussion. Fig. 10 and Fig. 11 demonstrate the comparison of factor effects regarding merchant ships of different ice classes.

In Fig. 10, it shows *OR* values of influencing factors regarding different ice classes. Unsurprisingly, the factor effect varies for ships with different ice classes. The trend of the factor effect of high ice class ships is similar to the entire database. Ridged ice concentration has the most impact on high ice class ships, but level ice concentration is the factor that influences the need for IB assistance the most for low ice class ships. Furthermore, wind impact is not statistically significant for low ice class ships. This can be explained as wind is a leading force for harsh ice conditions, and low ice class ships usually get IB assistance before entering such a severe condition.

In Fig. 11, it shows how the factor effect changes along the change of ship ice class. For ships with low ice classes, there is a substantial increase in the influence of level ice concentration. It is observed that the effect of level ice concentration overrules the influence of other factors for ships with low ice class, constituting 56.2% of the overall impact on the need for IB assistance. Although ridged ice concentration still has a relatively important impact for ships with low ice class, accounting for a weight of 13.1% in influencing the IB assistance need, its effect is mitigated by level ice concentration. This can be explained as ships with 1B, or lower ice class would stop before entering more challenging ice conditions, like ice ridges, because of the safety consideration (Kuuliala et al., 2017).

4.3. *Effectiveness evaluation of the identified factors*

To bridge the research gap discussed in Section 2, a relatively comprehensive list of influencing factors is identified (see Fig. 9) and analyzed by logistic regression. To evaluate the effectiveness of the

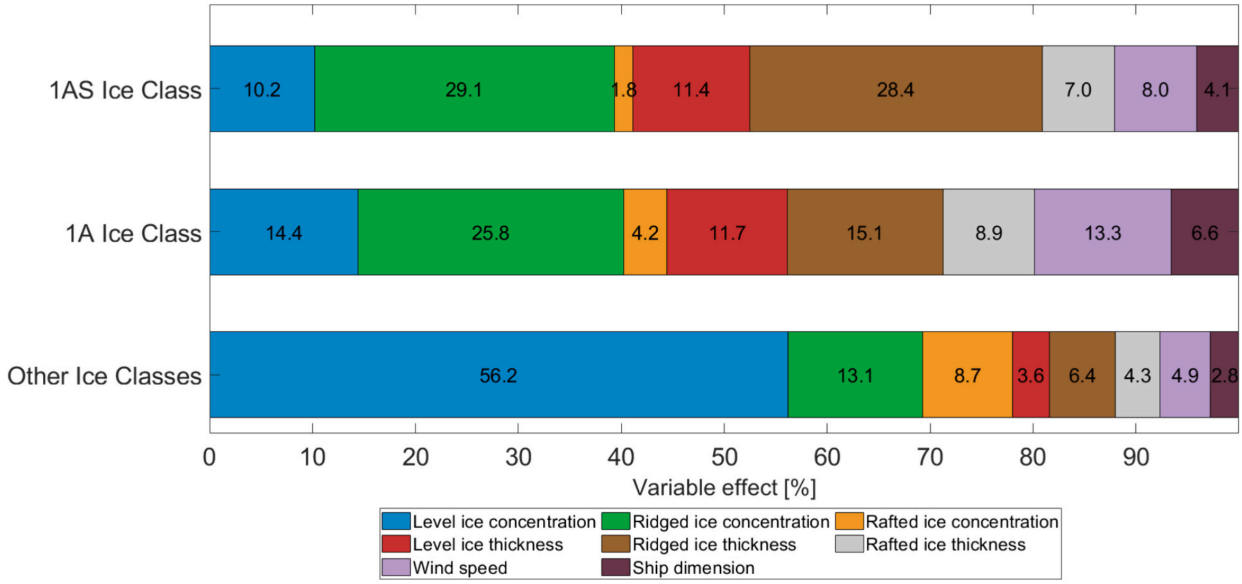

Fig. 11. Relative effect comparison of different ice classes

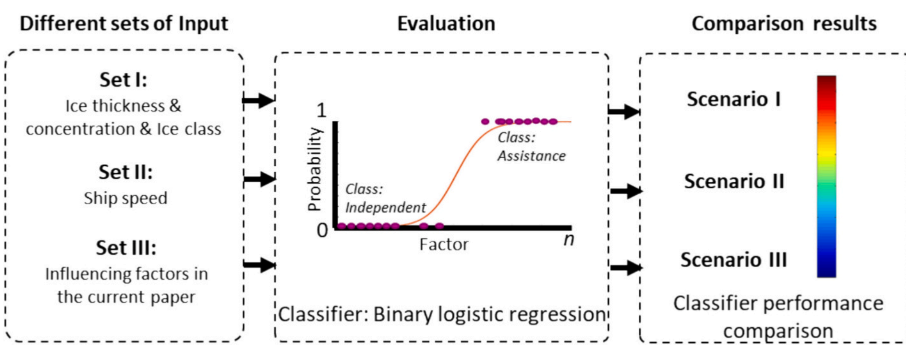

Fig. 12. The method of influencing factors performance comparison.

identified factors in classifying different navigation modes, logistic regression classification performance using different input factors is measured.

Specifically, the classification performance of the model is measured by using identified factors in Fig. 9 and two sets of factors in Table 2, respectively, and the results are compared. The confusion matrix and the area under the receiver operating characteristic curve (AUC) are applied to present the classification capability. The comparison method and results are descried in the following sections.

4.3.1. Effectiveness comparison method for navigation modes classification

In Fig. 12, it illustrates the comparative method, consisting of three steps. The first step is to prepare three different sets of factors as input for the classifier. Sets I and II present factors mentioned by existing studies in Table 2. Specifically, Set I presents ice concentration, thickness, and ship ice class. Set II presents ship speed. Detailed illustrations can be referred to in Table 2 and Section 2.1. Set III presents the factors identified in the current paper, including concentration and thickness of level ice,ridged ice, and rafted ice, snow thickness, wind speed, ship ice class, ship dimension, and ship type, see Fig. 9. The corresponding data come from the database in the current paper. Then, different sets of factors are used to feed logistic regression separately. By assessing different sets of factors, the classifier can perform differently regarding the classification of navigation modes. Finally, the confusion matrix and AUC results are compared to measure the effectiveness of different sets of factors.

The confusion matrix is a table that visualizes the performance of a classifier (Fawcett, 2006). As shown in Table 7, the matrix presents how well the classifier can distinguish different classes. Accuracy, precision, recall, and F1-score can be calculated based on the confusion matrix. See Eqs. (3)–(6). The higher the values, the better the performance of the classifier.

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} = \frac{TP + TN}{P + N} \tag{3}$$

$$Precision = \frac{TP}{TP + FP} = \frac{TP}{Total\ classified\ as\ assistance\ operation} \tag{4}$$

$$Recall = \frac{TP}{TP + FN} = \frac{TP}{Total\ actual\ assistance\ operation} \tag{5}$$

Table 7
Confusion matrix visualizing classification performance.

	Classification assistance operation	Classification independent operation
Actual assistance operation (*P*)	True positive (*TP*)	False negative (*FN*)
Actual independent operation (*N*)	False positive (*FP*)	True negative (*TN*)
Note:	*P* presents positive (Assistance operation); *N* presents negative (Independent operation).	

$$F1 - score = 2*\frac{Precision*Recall}{Precision + Recall} \tag{6}$$

Except for accuracy, precision, recall, and F1-score, AUC is also measured, a common index used to evaluate the classifier performance (Fawcett, 2006). AUC is the area under the receiver operating characteristic (ROC) curve, generally varying from 0.5 to 1. If AUC is 0.5, it demonstrates the classifier is only as good as the chance model. Generally, an AUC value ranging from 0.7 to 0.8 is considered acceptable; 0.8 to 0.9 is considered excellent, and >0.9 is considered outstanding (Mandrekar, 2010).

To measure AUC, the ROC curve needs to be plotted first. ROC is a two-dimensional graph in which the y-axis plots the true positive rate (*TPR*), and the x-axis plots the false positive rate (*FPR*). Based on various classification thresholds ranging from 0 to 1, *TPR* and *FPR* can be calculated according to Table 7 and Eqs. (7)–(8). The detailed information on ROC curve can be referred to (Fawcett, 2006; Halimu et al., 2019). Once ROC is plotted, AUC can be calculated based on the trapezoid rule, Eq. (9).

$$TPR = \frac{TP}{P} = \frac{TP}{Total\ actual\ assistance\ operation} \tag{7}$$

$$FPR = \frac{FP}{N} = \frac{FP}{Total\ actual\ independent\ operation} \tag{8}$$

$$AUC = \int_0^1 [FPR(t)]*[dTPR(t)]dt \approx \sum_1^N 0.5*(TPR[i] + TPR[i-1])*(FPR[i] - FPR[i-1]) \tag{9}$$

Where *i* presents the point on the ROC curve, and *N* presents the total number of points on the curve.

4.3.2. Effectiveness comparison results for navigation modes classification

Following the above method in Section 4.3.1, Table 8 shows the accuracy, precision, recall, and F1-score. Fig. 13 visualizes the AUC value, which is the area under the ROC curve.

In Table 8, it is observed that the classifier using factors in the current paper (as shown in Fig. 9) has the best classification performance, with 0.808 accuracy, 0.810 precision, 0.808 recall, and 0.807 F1-score. This is followed by the classification performance under the Set I (accuracy = 0.740, precision = 0.767, recall = 0.740, F1-score = 0.732). The performance under Set II is the worst. Compared to the result of Sets I and II, by considering the factors in Fig. 9, accuracy, precision, recall, and F1-score can be improved by at least 9.2%, 5.6%, 9.2%, and 10.3%, respectively.

In Fig. 13, the yellow line shows the ROC curve using the identified factors in the current paper (as shown in Fig. 9). The navy line shows the curve using factors in Table 2 Set I, and the green line indicates the curve using factors in Table 2 Set II. The AUC value is presented by calculating the area under each curve. The AUC comparison result also shows that the classifier using factors in the current paper has the best performance, with AUC equals to 0.874. Compared to the performance using the Set I (AUC = 0.803) and Set II (AUC = 0.690), AUC increases by at least 8.8%.

Therefore, based on the result comparison, we can conclude that the IB assistance need can be estimated more accurately by considering the identified influencing factors listed in Fig. 9. Although ship speed reflects operational conditions (e.g., the combined influence of ice conditions and ship conditions), using this indirect threshold solely as an estimation for IB assistance need is not the best option.

Table 8
Effectiveness comparison of different sets of factors

	Accuracy	Precision	Recall	F1-score
Performance using factors in Table 2 Set I	0.740	0.767	0.740	0.732
Performance using factors in Table 2 Set II	0.626	0.630	0.626	0.622
Performance using factors in Fig. 9 Set III	**0.808**	**0.810**	**0.808**	**0.807**

5. Limitations and future work

The paper presents a data driven approach to investigate the influencing factors and their effect on estimating the need for IB assistance in the Baltic Sea. However, as a starting step in quantitatively analyzing and understanding the factors and the reasoning behind human-made decisions, the proposed approach poses some limitations.

Firstly, the established dataset presents various ice conditions including thickness and concentration of different types of ice. However, extending the parameter set, including dynamic ice, ice compression, brash ice, or ice floes, can be considered, if the needed data are possible to obtain directly, or to derive from other data. For instance, a vessel navigating through thick level ice may find opportunities to reverse and repeatedly ram into the ice to break its way. However, dynamic ice around a vessel would significantly limit its movement, specifically when moving towards the midship section, because the broken channel would close, and dynamic ice would pose additional resistance. Therefore, the consideration of the additional factors could provide diverse findings. As a future work, various ice data source integration can be carefully considered. For instance, collecting and merging ice data from satellite images, ice observations and multiple forecasting models might be an option.

Secondly, the data analysis does not consider seasonal, yearly, and regional variations in operational conditions. The effect of parameters directly or cumulatively affecting ice structure and properties (e.g., freezing and melting cycles) would vary through seasons and years. The consideration of the above variations may lead to different results. For example, level ice may behave differently in cold winter months compared to warmer melting periods, thereby affecting the estimation of IB assistance need. Furthermore, the findings from this study focus on the Baltic Sea. Regional difference also plays a significant role, as external conditions and decision-making policies vary. The influencing factors and their effects may vary across different areas. Therefore, the investigation on other ice-covered waters (e.g., Arctic area) should be a sperate study in the future. Since the dataset is scalable, an extended data analysis by adopting the proposed approach to account for the above variations can be conducted when the necessary data becomes available.

Thirdly, as mentioned in Section 3.1, to present external conditions and traffic volume, AIS data and HELMI data are integrated. However, due to the varying resolution of AIS data and HELMI data, it is impossible to precisely integrate operational conditions with each traffic data point for all trips in the Baltic Sea. As a simplification, we assume that the external conditions remain constant around the vessel within the resolution of HELMI model. While 1 nm* 1 nm is a good resolution for an ocean model, it remains too coarse to accurately represent external conditions from a ship's perspective. Given this consideration, one potential future study should involve researching how to bridge the gap between the varying demands for data resolution across different fields. For instance, to present more detailed external conditions for ship operation analysis, collecting on board observed data within a 1 square nautical mile area would be necessary.

Finally, this study assumes that navigational patterns resulting from human made decisions are reflected in the observed trips, but a full-scale human factor study could help to better understand the efficacy of the approach. The effect of navigational experience can be analyzed within different navigational scenarios, using the factors identified in this study as a foundation for human factor analysis.

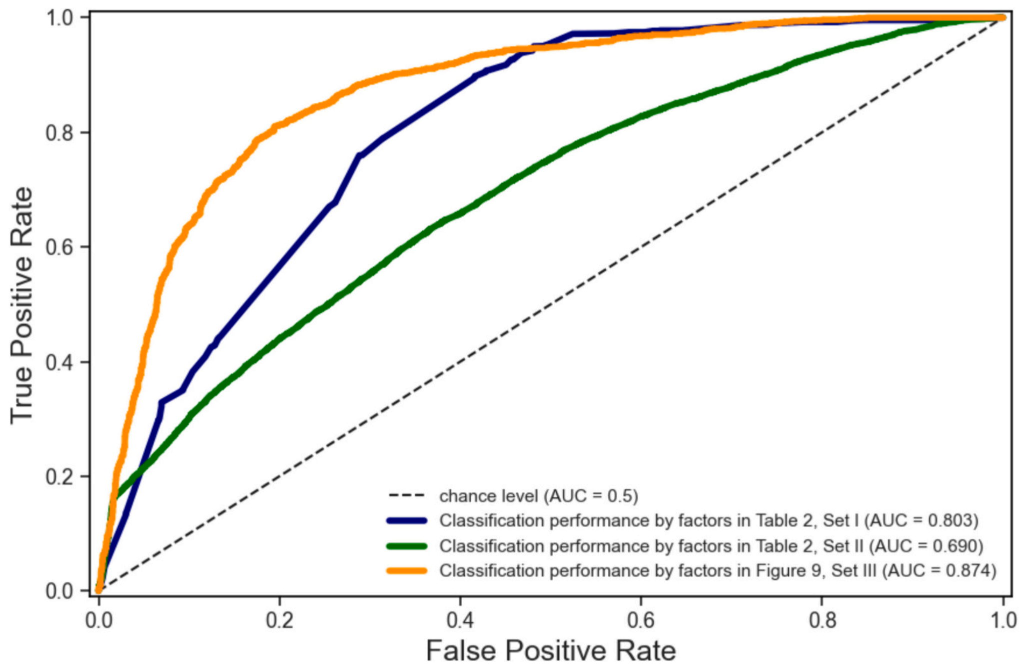

Fig. 13. AUC comparison using different sets of factors

6. Conclusions

This study proposed a data-driven framework for influencing factors analysis regarding navigation mode determination. This is the first time that the quantitative knowledge of how different factors affect the need for IB assistance was captured and discussed based on data. A novel database containing 15 factors presenting various operational scenarios for different navigation modes was established, and navigation mode classification was modeled as a function of the above factors. The results indicate that ice factors, environment factors, and ship specifications influence navigation mode determination simultaneously. Specifically, ridged ice concentration has the most significant impact, followed by level ice concentration. Compared to ridged and level ice, rafted ice thickness and concentration have minor effect on the IB assistance need. The analysis for fixed ice class indicates that for ships with low ice class, level ice concentration overrules the effect of all other factors, accounting for 56.2% of the overall impact. In actual life, ships with low ice class needs to be assisted by IB before encountering extremely harsh conditions, like the area covered by ridged ice. The findings aligned well with the current empirical knowledge. Except for quantitatively reflecting the actual operational scenarios well, the effectiveness evaluation of influencing factors demonstrates that the identified factors (see Fig. 9) enable a machine learning model to classify different navigation modes automatically. Compared to the existing used factors (see Table 2), the classification performance is improved by at least 5.6%. Overall, the study's outcomes underline the importance of data-driven research in winter navigation.

CRediT authorship contribution statement

Cong Liu: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ketki Kulkarni:** Writing – review & editing, Supervision. **Mikko Suominen:** Writing – review & editing, Supervision. **Pentti Kujala:** Writing – review & editing, Supervision, Resources. **Mashrura Musharraf:** Writing – review & editing, Supervision, Resources, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

We declare that we have no financial or personal relationships with others or organizations that can inappropriately influence our work. There is no professional or other personal interest of any nature or kind in any product, service, and/or company that could be construed as influencing the position presented in, or the review of, our work.

Data availability

Data will be made available on request.

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Appendix A. Appendix

Algorithm A.1. Logistic regression algorithm for coefficients determination

Initialize:

1. Let X be the matrix of input features, with each row representing a data point (x) and each column a feature, see Table A1.
2. Let y be the vector of target values (binary outcomes: Independent navigation or Assistance operation).
3. Choose a learning rate alpha and iterations number for the model training process.
4. Initialize the vector of coefficients b (including the intercept term) with zeros.

Output:

OR value of x, and the corresponding classified target value $\hat{y}$.

Process:

1. Add an intercept term to X:
   Prepend a column of ones to the matrix X, $X = np.insert(X, 0, 1, axis = 1)$
2. Perform gradient descent:
   α = learning rate
   ε = convergence threshold
While not converged:
   2.1. Calculate the current predictions:
      Compute $z = X * b$, where '*' denotes matrix multiplication.
      Define Function sigmoid (z): return $\frac{1}{(1 + np.exp(-z))}$
      Apply the sigmoid (z) to get predicted probabilities: $h = sigmoid(z)$
   2.2. Calculate the gradient:
      The gradient is the partial derivative of the cost function with respect to each coefficient. It can be computed as $gradient = (1/m) * (X^\wedge T * (h - y))$, where '$^\wedge T$' denotes matrix transpose and 'm' is the number of x.
   2.3. Update the coefficients:
      Adjust each coefficient by subtracting alpha times the corresponding gradient:
      $b = b - \alpha * gradient.$
   if norm(gradient) < ε:
      converged = True
3. The coefficients b at the end of this process are the estimated regression coefficients.
4. To calculate the OR value:
   For each coefficient in b, calculate the OR as the exponential of the coefficient, $np.exp(b)$

Algorithm A.2. The process of calculating VIF

Initialize:

Dataset D with X Features

Output:

X_{ram} Selected Features

Begin:

1. Calculate VIF:
   $Def\ calculate\_VIF$:
      For each X_i in X:
         $R_{sqaured} = calculate\_R_{sqaured}(X_i)$
         $VIF_i = \frac{1}{1 - R_{sqaured}}$
2. Calculate $R_{sqaured}$:
   $Def\ calculate\_R_{sqaured}()$:
      Regress each X_i against all other $X_{\sim i}$: $X_{i\_reg} = regress(X_i, X_{\sim i})$
      $R_{sqaured} = X_{i\_reg}.R_{sqaured}$
3. Remove multicollinearity feature(s):
   For each X_i in X:
      If $VIF_i > 5$, X_i is identified as a feature contributing to multicollinearity,
      $Resolve\_multicollinearity\_method$ (X_i)
4. Recalculate VIF:
   $recalculated\_VIF$ = $calculate\_VIF(X_{ram})$
   While any ($VIF_i > 5$ for VIF_i in $recalculated\_VIF$):
      Remove multicollinearity feature(s)

Table A1
Data format regarding navigation mode classification

Case	Level ice concentration	Ridged ice concentration	Rafted ice concentration	…	Ship ice class	Class
1	Numerical value	Numerical value	Numerical value		Categorical value	Yes
2	Numerical value	Numerical value	Numerical value		Categorical value	No
…	…	…	…	…	…	…
m	Numerical value	Numerical value	Numerical value		Categorical value	Yes
Note:	m is the number of cases.					

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