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# Identification of the Needs of Shipmasters and Shipping Stakeholders Towards Ship Safety Score for Shipping Safety Based on Logistic Regression Model

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***Abstract***. *An essential component of Indonesia's marine industry is shipping safety. This research aims to determine how important a vessel's safety score is as a potential indicator for reducing the probability of maritime accidents. To determine the meteorological variables that significantly impact ship accidents, we created a logistic regression model using survey data obtained from skippers of vessels operating within Indonesia. Furthermore, the study's findings demonstrate the critical need for objective assessment standards to raise shipping safety. This study offers important new information on creating and implementing thorough safety score criteria for Indonesian sailing license issuance.*

*Keyword: shipping safety, safety score, logistics regression, weather*

***Abstract.*** *Komponen penting dalam industri kelautan Indonesia adalah keselamatan pelayaran. Penelitian ini bertujuan untuk menentukan seberapa penting skor keselamatan kapal sebagai indikator potensial untuk mengurangi kemungkinan kecelakaan maritim. Untuk menentukan variabel meteorologi yang secara signifikan mempengaruhi kecelakaan kapal, kami membuat model regresi logistik dengan menggunakan data survei yang diperoleh dari nakhoda kapal yang beroperasi di Indonesia. Selain itu, temuan studi ini menunjukkan kebutuhan kritis akan standar penilaian yang obyektif untuk meningkatkan keselamatan pelayaran. Studi ini menawarkan informasi baru yang penting dalam menciptakan dan menerapkan kriteria penilaian keselamatan yang menyeluruh untuk penerbitan izin berlayar di Indonesia*

*Keyword: keselamatan pelayaran, skor keselamatan, regresi logistik, cuaca*

## INTRODUCTION

According to the Minister of Transportation (2018), 40% of global commerce routes travel through Indonesia, making Indonesian waters home to some of the densest shipping conditions in the world. Spread across a vast coastline, Indonesia boasts thousands of islands and hundreds of harbors, making it a hub for maritime activity. The shipping environment surrounding Indonesia is difficult due to the diverse topography and geography of the surrounding seas. Encompassing shallow waters, tight straits, and the highest seas, Indonesia's enormous and varied marine region makes it the world's biggest archipelago. This means that in order to maximize trade and mobility within the nation, shipping management and safety are vital issues. The weather plays a significant role on the likelihood of ship accidents [1][2][3] Poor weather can be a key contributing factor to shipping accidents, according to a number of earlier research [4][5][6][7]. Ships operating in Indonesian waters frequently encounter extreme weather conditions, such as strong winds, huge waves, and dense fog. These meteorological conditions have a significant impact on a ship's capacity to navigate and maneuver, which might raise the possibility of mishaps or accidents [8][9][10][11]12].

The Indonesian region has substantial weather conditions and heavy shipping, which raises the risk of ship accidents. According to statistics data, the number of ship accidents in Indonesia has been rather high in recent years [13][14]. Mistakes made by people, defective machinery, inclement weather, and other circumstances can result in a variety of incidents, from collisions to ship sinkings. The information pertaining to ship mishaps makes it abundantly evident that Indonesian maritime safety requires significant attention.

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In Indonesian waters, standardised Standard Operating Procedures (SOPs) pertaining to vessel sailing permits ought to ideally accommodate heavy shipping and noteworthy weather situations. SOPs must be precise and consistent in order to guarantee that ships operating in Indonesian waters follow accepted safety guidelines. Thus, the goal of this study is to determine the variables that affect the value of shipping safety. To that end, data from questionnaires will be gathered from shipping industry participants. Furthermore, this research will examine the urgency with which users require ship safety scores. Data on past ship accidents and the current state of the Standard Operational Procedure (SOP) for ship sailing permits in Indonesia will be used to highlight this urgency. It is therefore anticipated that this research would shed more light on the variables influencing maritime safety and prioritize the requirements for enhancing safety in Indonesian seas.

## METHOD

Both quantitative and qualitative approaches were used in this study. The significance of the ship safety score is examined in detail using the quantitative approach to analyze the captains' survey data. The second goal of this research, to thoroughly analyze the urgency of user needs for a ship safety score by data analysis from survey findings and the current conditions of SOPs for sailing licenses in Indonesia, is being accomplished in the meantime through the application of the qualitative technique. The most important meteorological factors and skippers' experiences with weather-related disruptions were among the survey data gathered. In order to quantify the survey data for future analysis, it was transformed into numerical data. In this instance, it is possible to determine the link between the variables, particularly the ways in which particular variables may affect ship accidents. Equation 1 [15] displays the Pearson correlation, which illustrates the linear link between a number of variables and the value of shipping safety.

$$\mathbf{r} = \frac{\mathbf{n}(\sum \mathbf{xy}) - (\sum \mathbf{x})(\sum \mathbf{y})}{\sqrt{[\mathbf{n}\sum \mathbf{x}^2 - (\sum \mathbf{x})^2][\mathbf{n}\sum \mathbf{y}^2 - (\sum \mathbf{y})^2]}} \quad (1)$$

A logistic regression model was then constructed using the survey data. To determine the likelihood of disruption based on vessel and weather factors that had been taken into account in the survey questions, a logistic regression model was constructed. We can determine the correlation between weather, vessel attributes, and the likelihood of a shipping interruption by using the survey data; this will yield important insights that will help enhance shipping safety in the Indonesian region. In addition, a comprehensive analysis of the urgency of user needs for vessel safety scores was also conducted through the analysis of data from the survey results, which was then contrasted with the existing SOP conditions for sailing permits in Indonesia. In this way, we can understand the extent to which the existing SOPs reflect and fulfil user needs in terms of shipping safety. The results of this analysis can provide a strong basis for recommending changes or improvements in the existing SOPs to make them more effective in maintaining shipping safety in Indonesian waters.

## RESULT AND DISCUSSION

Factors influencing a ship's safety rating can be found in Figure 1's first graph displays the total number of answers from each province. The province that received the most responses was Southeast Sulawesi, which was followed by South Sulawesi and East Java. This could mean that respondents from these provinces have dealt with difficult maritime conditions for a longer period of time or that there is greater maritime traffic in these areas. Provinces like Bangka Belitung and Bali, on the other hand, had less responses; this could be because of their smaller populations or decreased maritime activity.

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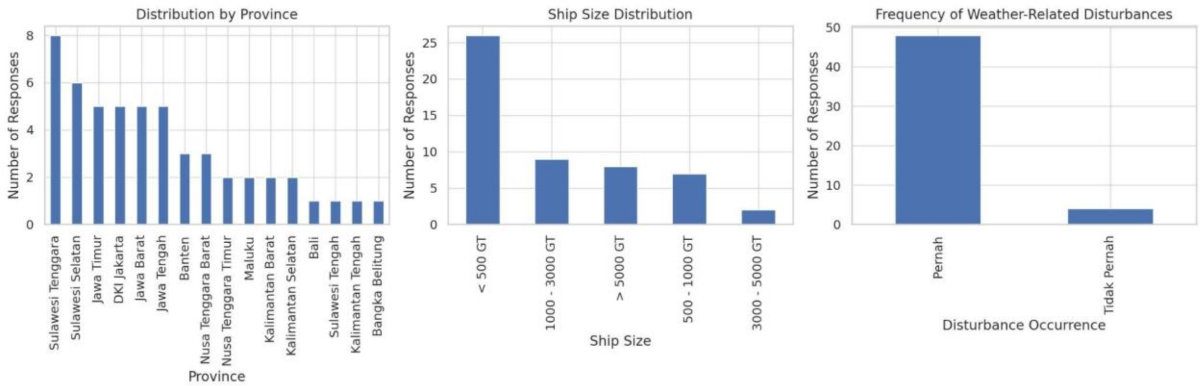


***Figure 1**. Results of the survey broken down by weather disturbances, vessel size, and province distribution*

The size distribution of the vessels taking part in the survey is shown in the second graph in Figure 1. The majority of the vessels that answered were under 500 GT, suggesting that smaller vessels are more likely than bigger ones to be involved in maritime operations or to be more vulnerable to weather-related disruptions. Larger vessels received much fewer responses, which can mean that they are underrepresented in the poll or are better prepared to withstand bad weather. The frequency of disruptions caused by weather is displayed in the third graph in Figure 1. Just a small percentage of respondents said they had never experienced disruptions connected to weather, with the majority indicating they had ('In the past'). The significant percentage of participants who have encountered weather-related delays attests to the fact that these disruptions are a frequent issue in marine operations, underscoring the significance of efficient planning and readiness for weather conditions.

The data presented, as indicated by Figure 1, emphasizes the significance of comprehending the regional distribution and vessel size in relation to maritime safety, together with the frequency of weather-related disruptions in maritime operations. These studies can be used to support decisions aimed at improving the safety of smaller vessels—which seem to be more frequently impacted by unfavorable weather conditions—and to allocate resources to locations with greater levels of reported interruptions. The study participants strongly ranked 'High Tide' as the most influential weather element on maritime safety, as seen by the graph labeled "Most Influential Weather Parameter" in Figure 2. According to the graph, "High Tide" was cited by over 30 responders as the meteorological component that had the biggest impact. It is evident that respondents to the survey view high waves as a more significant threat than they do from the other two parameters, "Strong Winds" and "High Current Speed," which each garnered only a third or fewer of the replies for "High Tide."

In particular, 'High Current Speed' garnered the fewest responses, indicating that it is regarded as the least influential component of the three, while 'Strong Winds' appears to be the second most impactful factor, with significantly fewer responses than 'High Tide'. The data quantitatively indicates respondents' perceptions of the wave heights that have the greatest influence on maritime operations, based on the graph depicting the "Impact of High Waves" in Figure 2. As we can see, the most respondents identified waves with heights between 1.5 and 2 meters as having the most influence. Approximately 14 respondents identified this range as being the highest. Waves that measured between two and three meters in height came next, and about twelve respondents thought these were noteworthy. According to a quantitative analysis of this data, waves between 1.5 and 2.5 meters are typically the most problematic or disruptive for respondents. This could be a reflection of the wave conditions that respondents most commonly encounter or the design and durability features of the vessels that they typically use. While waves over 2.5 meters may happen less frequently or the vessels may be better prepared to withstand them, waves lower in height might not be seen as dangerous.

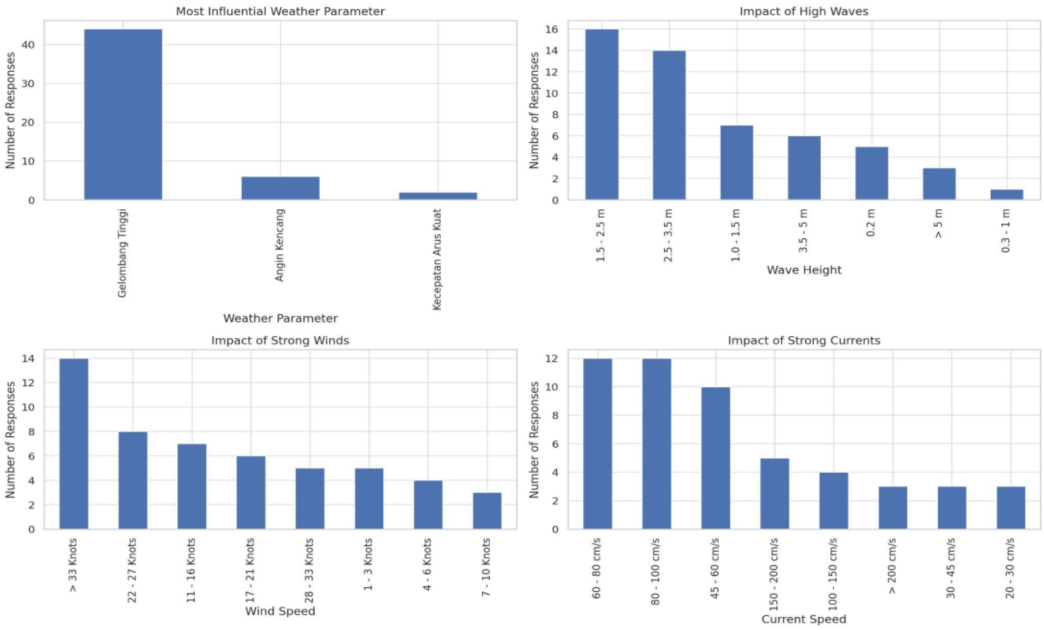


*Figure 2. Results of the survey based on perturbations in meteorological parameters.*

Winds over 33 knots are shown in Figure 2's "Impact of Strong Winds" graph as the category that drew the most responses, suggesting that these extremely high wind speeds are thought to have a major influence on marine activities. In terms of numbers, fewer responses are received in the categories with lower wind speeds. For instance, reactions were lower for wind speeds between 22 and 32 knots and between 11 and 21 knots than for winds over 33 knots. This represents the belief that very high winds are far more dangerous and likely to seriously impair vessel operations, even though lower speed winds may still have an effect. Respondents paid the least attention to winds of less than 10 knots, which may indicate that they thought these speeds would not have a significant impact on maritime operations or safety. This might be the case since ships are built to withstand winds of up to a particular speed without experiencing too many issues. In conclusion, survey participants felt that winds over 33 knots were a significant risk factor and may have a significant effect on marine safety.

Respondents' opinions of how current speeds impact marine operations are shown in Figure 2's "Impact of Strong Currents" graph. According to the findings, currents traveling at a speed of between 4 and 6 cm/s are thought to have the most influence; approximately 10 respondents gave this opinion. Following this, currents of 6–8 cm/s received about equal numbers of replies, suggesting that they had a comparable impact on respondents' perceptions. It's interesting to note that the number of answers decreased significantly for currents faster than 8 cm/s. Much less attention was paid to currents moving at speeds of 8–10 cm/s and faster. This could mean that the vessels the responders operate are capable of handling stronger currents without experiencing major issues, or it could mean that they hardly ever encounter currents of these speeds. Conversely, the reduced number of replies for current speeds between 0 and 4 cm/s indicates that these speeds were also thought to have less of an effect. This might be the case since smaller currents don't significantly obstruct vessel operations or navigation. The analysis of the data leads to the conclusion that current velocities falling between 4 and 8 cm/s are thought to provide the greatest risk and impact on maritime safety. Currents in this range may be more challenging for vessels to handle, or it could be that because these are the currents that are encountered most frequently in day-to-day operations, respondents are more likely to report them as impactful. A logistic regression model, which uses one or more independent variables to predict the probability of an event happening, is the type of model that was constructed. These are the model's specifications. Based on a number of independent variables, a logistic regression model is constructed to predict if a skipper has encountered weather-related disturbances while at sea. These variables include the size of the vessel the skipper operates, the skipper's province of residence, and the degree of disruption caused by specific weather conditions like large waves, strong winds, and strong current speeds. The model makes use of logistic regression techniques, a well-liked statistical approach for estimating an event's probability given a set of independent factors. In order to ensure that the model has strong generalizability, the data used for training and testing the model is divided into two portions: 70% of the data for training and 30% for testing. This approach is widely used in machine learning. According to the regression model, there is a strong negative link between wind speed and disturbance experience, but a positive correlation between vessel size and current speed. This is intriguing since it implies that bigger boats and boats traveling against strong currents are more likely to become stranded. According to the captain, big waves are the most important weather parameter, which is consistent with current maritime safety regulations, according to additional analysis. The regression model's low coefficient for this weather parameter, however, suggests that other variables might be more important in determining vessel safety.

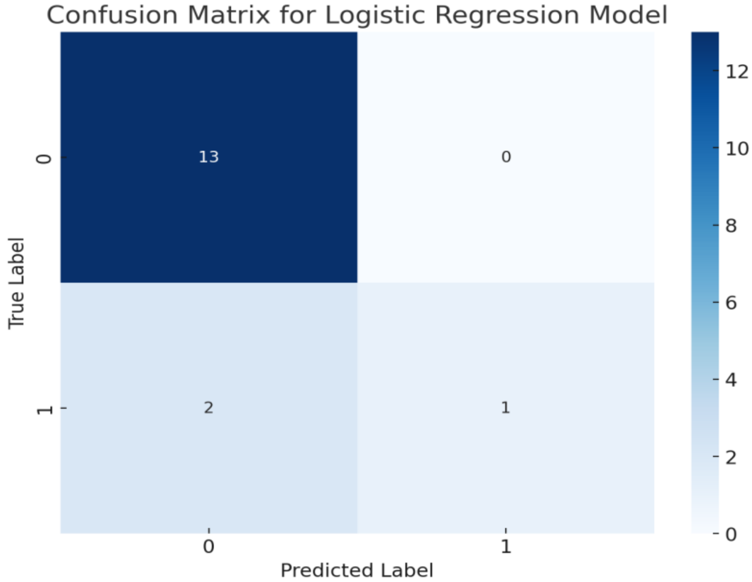


Figure 3. Perform the regression logistic model.

A helpful tool for comprehending the classification model's performance is the confusion matrix shown in Figure 3. It shows how the value predicted by the model compares to the true value, which in this case is whether the weather affected the skipper. The two rows and two columns of the confusion matrix in this instance reflect the two classifications, "Never Experienced Disturbance" and "Experienced Disturbance.". The entire number of samples in the test set is represented by the total value of 16 in this matrix. This shows that 16 observations make up 30% of the total dataset that was used for testing. The model was able to correctly anticipate the majority of these sixteen cases. The number of accurate forecasts that the skipper is not impaired is indicated by the numbers in the top left box, and the number of accurate predictions that the skipper is impaired is indicated by the values in the bottom right box. There are two off-diagonal boxes (top right and bottom left) that show how many forecasts were wrong. The high percentage of accurate forecasts compared to inaccurate ones suggests that the algorithm works well, particularly in determining situations in which the skipper is not hampered by bad weather.

In order to evaluate the model's performance in differentiating between the two categories and identify potential areas for improvement, it is crucial to interpret the confusion matrix. For instance, the model may be more likely to classify cases as "Never Impaired" if the value in the bottom right box (correct prediction for "Ever Impaired") is lower than the value in the top left box (correct

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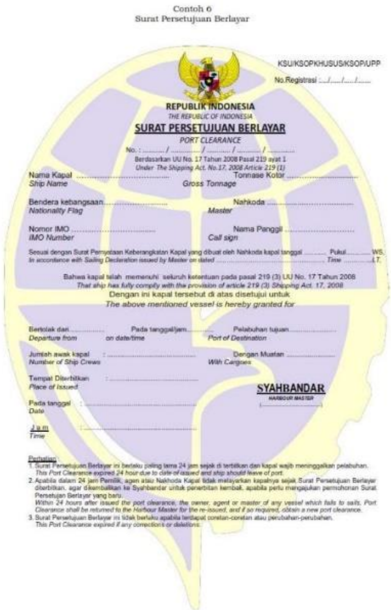
prediction for "Never Impaired"), which could be an area for further model refinement. While evaluating the risk of shipping, ships and maritime weather have a significant role. The chance of an event is influenced by the vessel's condition, particularly its age, size, and maintenance status. Similarly, meteorological factors that are evident in the collected data, like large waves, wind, and currents, have an immediate impact on the safety of ships. The combination of these factors should be covered in this research as a crucial foundation for creating a trustworthy safety score that can accurately forecast possible hazards. Between 2007 and 2023, 221 maritime accidents were reported to the National Transportation Accident Commission (NTSC). Sixty-one percent, or 135 cases, were classified as extremely serious. The most of incidents (33%) involved fire, with sinking (27%) and collision (20%) coming in second and third, respectively, and aground (17%) coming in third. The two main vessel types that the NTSC looked into the most were cargo ships and Ro-Ro passenger ships, which can carry both cars and people. The passenger, tanker, and container ships are listed below. As to Article 219 of Law No. 17 Year 2008 on Shipping, each sailing vessel must possess a Sailing Approval Letter (SPB) issued by the Syahbandar. Weather-related factors are taken into account while issuing this sailing approval letter. Furthermore, it is stated in Article 11 paragraph (8) of Minister of Transportation Regulation Number PM 28 Year 22 that delays in ship departure may be made due to weather-related reasons. According to Article 13, the syahbandar may refuse to issue an SPB based on a variety of factors, including c. water weather circumstances that could jeopardize the ship based on the ship's size and/or type.



Contoh 6
Surat Persetujuan Berlayar

KSU/KSOPKHUSUS/KSOP/UPP
No.Registrasi : ..../..../..../....

REPUBLIK INDONESIA
*THE REPUBLIC OF INDONESIA*
**SURAT PERSETUJUAN BERLAYAR**
*PORT CLEARANCE*
No. : ......../......../......../......../........
Berdasarkan UU No. 17 Tahun 2008 Pasal 219 ayat 1
*Under The Shipping Act. No.17. 2008 Article 219 (1)*

Nama Kapal / *Ship Name* ..................... Tonnase Kotor / *Gross Tonnage* .....................
Bendera kebangsaan / *Nationality Flag* ..................... Nahkoda / *Master* .....................
Nomor IMO / *IMO Number* ..................... Nama Panggil / *Call sign* .....................

Sesuai dengan Surat Pernyataan Keberangkatan Kapal yang dibuat oleh Nahkoda kapal tanggal ........ Pukul ........ WS.
*In accordance with Sailing Declaration issued by Master on dated* ........ *Time* ........ LT.

Bahwa kapal telah memenuhi seluruh ketentuan pada pasal 219 (3) UU No. 17 Tahun 2008
*That ship has fully comply with the provision of article 219 (3) Shipping Act. 17, 2008*
Dengan ini kapal tersebut di atas disetujui untuk
*The above mentioned vessel is hereby granted for*

Bertolak dari / *Departure from* ........ Pada tanggal/jam / *on date/time* ........ Pelabuhan tujuan / *Port of Destination* ........
Jumlah awak kapal / *Number of Ship Crews* : ........ Dengan Muatan / *With Cargoes* ........
Tempat Diterbitkan / *Place of Issued* : ........
Pada tanggal / *Date* : ........
Jam / *Time* : ........

**SYAHBANDAR**
HARBOUR MASTER

Perhatian:
1. Surat Persetujuan Berlayar ini berlaku paling lama 24 jam sejak di terbitkan dan kapal wajib meninggalkan pelabuhan.
*This Port Clearance expired 24 hour due to date of issued and ship should leave of port.*
2. Apabila dalam 24 jam Pemilik, agen atau Nakhoda Kapal tidak melayarkan kapalnya sejak Surat Persetujuan Berlayar diterbitkan, agar dikembalikan ke Syahbandar untuk penerbitan kembali, apabila perlu mengajukan permohonan Surat Persetujuan Berlayar yang baru.
*Within 24 hours after issued the port clearance, the owner, agent or master of any vessel which fails to sails, Port Clearance shall be returned to the Harbour Master for the re-issued, and if so required, obtain a new port clearance.*
3. Surat Persetujuan Berlayar ini tidak berlaku apabila terdapat coretan-coretan atau perubahan-perubahan.
*This Port Clearance expired if any corrections or deletions.*

Figure 4. Sample Sailing Approval Letter

There is currently no established standard that specifies the types of sea conditions that lead to ship accidents. No formula exists that determines the cutoff point or quantitative limit, like a ship safety score. As a result, the requirement for this safety score is quite urgent in order to satisfy current laws and SOPs. One of the factors taken into account before a Sailing Approval Letter is issued will be the requirement for this safety score. Additionally, reducing ship accidents at sea requires the application of this safety score. The confusion matrix indicates that the constructed logistic regression model has a high degree of accuracy in predicting non-risk events. This indicates that the ship safety score can be effectively derived from the model. It will be crucial to investigate in the discussion how this model may be enhanced and integrated with the current parameters. Some examples of how it can be improved include modifying the risk detection threshold and adding real-time data to dynamically update safety scores.

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This model can be a valuable tool in policy making as there is currently no defined method for calculating vessel safety scores for sailing licenses. The model's ability to close this gap and the ways in which maritime authorities can utilize it to impose more stringent operational standards and procedures—which will enhance safety and lower accident rates—should be covered in the conversation. There is a gap in the current maritime safety policy, as evidenced by the lack of a standardised calculation guiding a ship's safety score. The conversation should emphasize how urgent it is to create a formula that takes into consideration the previously listed variables. It might also provide suggestions for additional study that will evaluate the logistic regression model's efficacy using bigger data sets for validation and in varying operational scenarios. Consequently, it is imperative to underscore that the creation and execution of a data-driven ship safety score constitutes a critical measure in guaranteeing secure navigation and efficient risk mitigation within the marine sector. The article should also encourage relevant stakeholders in the marine industry to take a more risk-based and data-driven approach when making decisions on maritime safety.

## CONCLUSION

The study's conclusions highlight how crucial it is to take meteorological conditions into account when calculating a vessel's safety score. Policymakers can create more effective policies to increase maritime safety in the Indonesian region by taking into account elements like ship size, large waves, wind speed, and strong currents. Further research with bigger sample sizes and more variables is advised in order to bolster model predictions and encourage data-driven decision-making.

## RECOMMENDATION

The small sample size and data imbalances that could have an impact on the findings are the study's primary limitations. In order to develop more reliable prediction models, future research could address these constraints by increasing the survey sample and adding real data on ship accidents. The need of incorporating weather variables into Indonesia's vessel safety score assessment system is reinforced by this study, which offers fresh insights into the weather aspects influencing shipping safety. It provides a step in the direction of a comprehensive strategy for managing marine risk.

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