

It has motivated the consolidation of human factors as a field of study in the maritime domain (Grech, Horberry and Koester, 2008), the adaptation of frameworks such as the Human Factors Analysis and Classification System (Galerikova, 2019), the use of systemic models of accident causation (Hollnagel and Götteman, 2004; Perrow, 1984), and, more recently, the incorporation of psychological and cognitive variables into safety assessment (Fan et al., 2023).

Most of this research, however, is directed at the vessel and the accident: identifying causal variables, classifying accident types and, increasingly, predicting them with statistical and machine-learning models (Uğurlu et al., 2020; Maceiras et al., 2024). Comparatively little attention has been paid to the other end of the emergency—the shore-based coordination centre, where a controller must turn a fragmentary alert into a coordinated response. Yet it is there that the consequences of an accident are managed in real time, under three pressures that define the work: incomplete information, time, and a cognitive workload that rises sharply the moment routine monitoring becomes an active emergency. Effective coordination depends on the controller's situational awareness—the perception, comprehension and projection of a rapidly evolving situation (Endsley, 1995)—which is known to degrade as mental workload rises in maritime settings (Müller-Plath, 2023) and to depend strongly on operator experience in search-and-rescue tasks (MacDonald et al., 2026). Mental workload is itself a measurable construct (Hart and Staveland, 1988), and the decisions taken under it are frequently made not by exhaustive analysis but by experience-based pattern recognition, as described by naturalistic decision-making research (Klein, 2008).

This lifecycle can be read as a sequence of phases: an initial failure on board; an alert that triggers a cognitive shift from routine to emergency; a coordination phase in which the centre allocates resources and logistics; and a critical decision whose outcome rests on whatever information is available at that moment. Each phase places distinct demands on the operator, and the human factor that pervades the causes of accidents reappears, transformed, in the response to them. Circadian and fatigue effects, well documented on board (Vinagre-Ríos et al., 2021; López López, 2023) and measured among shore-based control-room operators in Spanish coordination centres (Crestelo Moreno et al., 2023), apply with equal force to the controller on a long night shift.

Decision-support systems for search and rescue have developed considerably, but predominantly on the outward side of the problem: optimising search areas, allocating resources and estimating mission success, increasingly with artificial intelligence techniques (Otote et al., 2019; Laperrière-Robillard, Morin and Abi-Zeid, 2022); standardised methods also exist for communicating the on-scene safety status of a distressed vessel between ship and rescue centre (Nordström et al., 2016). These tools address how to plan and execute the search, and how to characterise the casualty, once the emergency is under way. Far less work has addressed the inward, cognitive side—how a controller allocates finite attention across the incidents under surveillance, and which of them are likely to demand the most coordination effort before that effort is actually incurred.

It is this gap that the present work addresses.

The Spanish Search and Rescue (SAR) region offers a demanding and well-documented setting in which to do so. Accidents there are investigated by the Spanish Commission for the Investigation of Maritime Accidents and Incidents (CIAIM) and emergencies are coordinated operationally by the Spanish Maritime Safety and Rescue Agency (Salvamento Marítimo). It is a fishing-intensive region in which earlier analyses of the same accident records have shown that compliance with the minimum safe-manning requirement and vessel characteristics—length, beam and age—are the variables most strongly associated with accidents, whereas visibility and sea state, often assumed to be decisive, are the weakest descriptors for this region (Maceiras et al., 2021; Maceiras et al., 2024). It is important to delimit the boundary with that earlier work. The previous studies used the same accident records to build predictive descriptors of risk aboard the vessel, classifying and forecasting accident types; the present work re-uses that empirical base deliberately, for continuity, but turns it to a different purpose—the first operational transfer of those findings to the shore-based coordination of the response. The earlier contribution was diagnostic and vessel-centred; this one is operational and controller-centred. Those studies established what structures the accidents; they did not translate that knowledge into a form usable at the coordination post.

The present work takes that step. Building on the same empirical base, it proposes a Coordination Demand Index (CDI): a transparent, parsimonious composite that maps the observable characteristics of an incident to an estimate of the coordination effort it is likely to require. The index is deliberately built around the information actually available to a controller, and is defined in two states—an *a priori* estimate from data knowable at the first alert, and an updated estimate once the emergency reveals further detail—so as to mirror decision-making under incomplete information rather than to assume away its central difficulty. Complementing the continuous index, the recurrent accident archetypes identified by clustering are mapped onto a three-tier screen-triage scheme, so that the incidents likely to be most demanding can be flagged for heightened attention. Finally, the index is placed in its operational context through a simple workload model that combines the official activity statistics of the coordination network with its staffing structure.

The aim is not to automate the controller's decisions but to support them. Consistent with the principle that technology must serve the human operator rather than supplant the judgement built on experience (Klein, 2008), the CDI and the triage scheme are conceived throughout as complementary aids—tools that direct scarce attention towards the situations that most warrant it, while leaving the decision where it belongs.

2. Methods.

This work adopts an integrative approach that connects empirical evidence from maritime accident analysis with the operational reality of emergency coordination in Search and Rescue (SAR) control centres. Two complementary data sources are combined: (i) official accident records, which characterise the

profile of severe incidents; and (ii) the national activity statistics and the staffing structure of the coordination network, which provide the operational denominator against which that profile is interpreted. From these, a Coordination Demand Index (CDI) is derived and proposed as a complementary aid to the controller's judgement, never as a replacement for it.

2.1. Data sources.

The accident sample is drawn from the reports of the Spanish Commission for the Investigation of Maritime Accidents and Incidents (CIAIM) for the Spanish SAR region over the period 2008–2017, the same regulatory window used in previous work (Maceiras et al., 2021; Maceiras et al., 2024). After retaining only incidents with complete information across the analysed variables, the working set comprises 276 accidents.

Operational context is taken exclusively from the annual reports published by the Spanish Maritime Safety and Rescue Agency (Salvamento Marítimo) for the corresponding years. Emergencies are coordinated from a network of 20 Maritime Rescue Coordination Centres (MRCC) covering a SAR area of approximately 1.5 million km². For the staffing model, five centres operate with three controllers per shift (Finisterre, Tarifa, Almería, Las Palmas and the National Centre, Madrid) and the remaining fifteen with two controllers per shift; the historical zonal/local distinction (CZCS/CLCS) has since been retired, all centres now being designated MRCC.

2.2. Variable coding.

Each accident is described by the variables routinely recorded in CIAIM reports: ship type, year of construction, wind force (Beaufort scale), sea condition (Douglas scale), swell height, visibility, day/night period, length, beam, gross tonnage, number of crew members, the cause of the accident (coded as human-factor influence) and whether the ship met the minimum safe-manning requirement. The full coding scheme follows the scales reported previously (Maceiras et al., 2024, Tables A1–A8).

Two coding considerations are made explicit. First, zero values in the source data arise from two distinct mechanisms: absence of the datum in the official report, and the variable being not applicable or not relevant to that incident (for example, the second vessel's dimensions when only one vessel is involved). These two mechanisms are treated separately and flagged, rather than being interpreted as a numerical zero. Second, where an accident involves two vessels, a single representative record per incident is retained, consistent with the treatment in Maceiras et al. (2024).

2.3. Variable importance.

The relative relevance of each variable was estimated with a random forest classifier (Breiman, 2001) trained to predict the type of accident, reproducing the methodology of Maceiras et al. (2024). Because impurity-based (Gini) importance is biased towards continuous, high-cardinality variables, permutation importance was used instead, which is unbiased in this respect and is the faithful analogue of the bias-corrected estimator employed in the earlier study.

The permutation analysis confirms the published finding: compliance with the minimum safe-manning requirement is the dominant variable, while visibility is effectively non-informative for this region. The human-factor variable emerges as co-dominant; however, because the involvement of the human factor is established *a posteriori*, during or after the emergency, it is deliberately excluded as an input to an early operational index (it would not be available at the moment of coordination) and is instead used as an interpretive reference.

2.4. Coordination Demand Index (CDI).

The CDI is a transparent composite that maps the characteristics of an incident to an estimate of the coordination effort it is likely to require. For incident i :

$$CDI_i = w_c C_{crew}(i) + w_y C_{year}(i) + w_s C_{size}(i) + w_n C_{night}(i) + w_w C_{wind}(i). \quad (1)$$

where each component $C(\cdot)$ is scaled to the interval [0, 1] in the direction of increasing coordination demand, and the weights w are the normalised permutation-importance values of the early-observable variables (minimum-manning ≈ 0.58 , year of construction ≈ 0.17 , size ≈ 0.19 , night ≈ 0.04 , wind force ≈ 0.02). The component directions reflect operational judgement informed by control-centre experience: undermanning increases demand (a vessel that has sailed short-handed has reduced capacity for self-management and depends more heavily on the centre); older vessels increase demand; night increases demand (delayed detection and operator fatigue). Vessel size enters as a minor component oriented towards greater consequence complexity and is subjected to sensitivity analysis.

A central design feature is that the index is defined in two states, mirroring decision-making under incomplete information:

- *A priori (monitoring / first report)*: only data knowable at that moment are used. The crucial point is that, although the actual manning status of a given vessel is unknown *a priori*, its type is known from AIS/registry data, and the empirical base rate of undermanning by vessel type is informative ($\approx 24\%$ for fishing vessels versus $\approx 5\%$ for passenger/cargo vessels; $\approx 20\%$ overall). The type-conditioned base rate therefore enters as the prior contribution of the manning component. For vessel types with too few records for a reliable rate, the overall rate is used and the uncertainty is flagged.
- *Updated*: once the emergency reveals the actual manning status, the prior is replaced by the confirmed value and the index is revised accordingly.

2.5. Incident typology and screen triage.

Alongside the continuous index, an unsupervised typology was produced by principal component analysis followed by k -means clustering ($k = 3$), reproducing the approach previously applied to this dataset. Three operational archetypes are obtained:

- **Cluster 1—small and older vessels:** short length, older construction, minimum safe-manning requirement not met, and the highest associated accident risk.
- **Cluster 2—large and modern vessels:** long length, recent construction, minimum safe-manning requirement met, with accidents linked predominantly to environmental conditions.
- **Cluster 3—fishing and recreational vessels:** small size, recreational or fishing use, predominant human-factor involvement and frequent operational errors.

These archetypes map naturally onto the demand tiers of the screen-triage scheme. The large, modern, well-manned vessels of Cluster 2 represent the low-demand (green) tier: they retain on-board capacity for self-management and their incidents are driven by external conditions rather than by manning or human factors. The undermanned, older vessels of Cluster 1 and the human-factor-laden fishing and recreational craft of Cluster 3 represent the elevated-demand (amber/red) tiers that warrant heightened attention. The continuous CDI refines this discrete typology; the “red” flag directs the controller’s attention and verification effort—or that of an assisting automated layer—without taking decisions on the controller’s behalf.

This triage logic is framed within the emergency lifecycle as it is experienced from the coordination centre—initial failure, alert phase, coordination, and a critical decision taken on partial data—so that the *a priori* state of the index supports the alert and coordination phases and the updated state supports the critical-decision phase as information arrives.

2.6. Operational workload model.

Independently of the accident records, the annual activity statistics and the staffing structure are used to size the coordination workload. The number of controller-shifts available per day across the network is obtained from the centre categories and the daily shift structure (three shifts per day: a 10-hour night shift and two 7-hour day shifts; controllers rotate on a three-days-on / three-days-off basis), giving 135 controller-shifts per day nationally (five centres with three controllers and fifteen with two, over three shifts: $5 \times 3 \times 3 + 15 \times 2 \times 3$). Dividing the coordinated-emergency volume by this denominator yields a raw average load per controller-shift, which is deliberately reported per centre and per zone rather than as a single national figure, given the pronounced heterogeneity between centres. Rather than treating all emergencies as equivalent, the CDI can aggregate demand within a defined set of incidents—for example, summarising the mean demand of each accident type within the CIAIM records—so as to distinguish not merely how many incidents occur but how demanding they are. Extending this complexity-weighted reading to the full flow of coordinated emergencies would require per-incident attributes that the centres record operationally but that are absent from accident-investigation data, and is therefore identified as future work. The model does, however, make explicit the coincidence between high-demand night-time incidents and the longer, fatigue-prone night shift.

Note: the annual emergency series is taken directly from the Salvamento Marítimo annual reports (2008–2016 stated explicitly as “emergencias atendidas”; the 2017 report aggregates persons attended rather than the emergencies total).

3. Development.

This section applies the methods of Section 2 in three steps. First, the empirical accident profile is characterised from the CIAIM records, including temporal patterns not reported in earlier work. Second, the Coordination Demand Index (CDI) and the incident typology are derived and turned into a screen-triage scheme. Third, the operational context of the coordination network is described from the official activity statistics, and a workload model is proposed. Throughout, the two data layers are kept in distinct roles: the CIAIM records, which the Commission investigates selectively on grounds of relevance, are used to characterise accident profiles; the Salvamento Marítimo statistics are used to describe the operational context in which coordination takes place. The two are not compared numerically, since the investigated accidents are not a defined fraction of the total coordinated emergencies.

3.1. The accident profile and its temporal patterns.

Across the 2008–2017 window, the working set comprises 276 fully documented accidents. Fishing vessels account for roughly 60% of the craft involved, consistent with the structure of the Spanish fleet and with previous findings (Maceiras et al., 2021; Maceiras et al., 2024). The most frequent accident types are flooding and operational accidents, followed by stranding and contact; the human factor is recorded as influencing about two thirds of cases, and roughly two fifths of accidents occur at night.

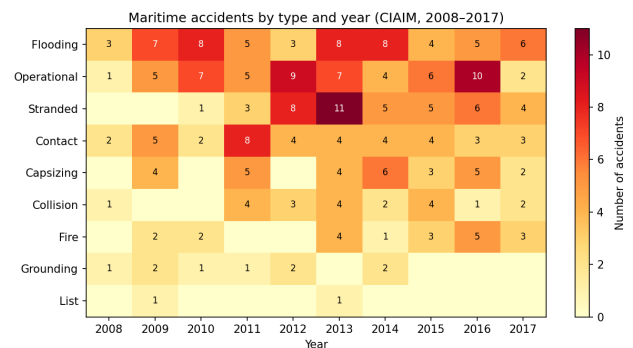


Figure 1: Maritime accidents by type and year (CIAIM, 2008–2017).

Two temporal views, not presented in the earlier studies, add operational value. The type-by-year heat map (Figure 1) shows how the composition of accidents shifts across the decade. The seasonality heat map (Figure 2) reveals clear month-of-year structure: flooding concentrates in spring, operational accidents build through the second half of the year with a peak in October, and strandings peak in January. These patterns are directly

actionable for a coordination centre, since they indicate when particular accident profiles become more likely and attention can be calibrated accordingly.

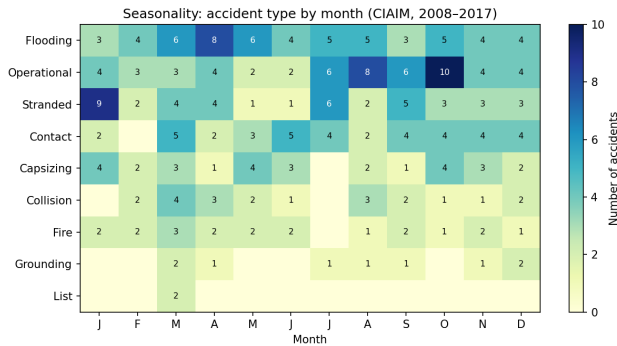


Figure 2: Seasonality: accident type by month (CIAIM, 2008–2017).

3.2. Variable importance and the Coordination Demand Index.

The permutation-importance analysis confirms and refines the published results. Compliance with the minimum safe -manning requirement is the dominant variable, with the human-factor variable emerging as co-dominant, while visibility is effectively non-informative for this region—in agreement with the conclusion of Maceiras et al. (2021, 2024) that visibility and sea state are the weakest descriptors here. As argued in Section 2, the human factor is excluded as an input to the index because its involvement is established after the fact and is therefore unavailable at the moment of coordination.

The resulting CDI distributes the incidents along a continuous demand scale (Figure 3). The upper quartile of the index concentrates the operationally most demanding configurations: around three quarters involve a manning shortfall and a clear majority occur at night, with a median vessel length of the order of 37 m and a median build year around 1990. The CDI surface over ship length and manning compliance (Figure 4, in the style of the three-dimensional representation of Maceiras et al., 2024) makes the gradient explicit: demand rises as vessels become smaller and as manning compliance fails, with age, night and wind acting as secondary modifiers.

In its *a priori* state, the index uses the type-conditioned base rate of undermanning as the manning prior—about 24% for fishing vessels against about 5% for passenger and cargo vessels—and updates to the confirmed value once the emergency reveals the actual manning status.

The robustness of the index to its weighting choices was examined by recomputing the CDI under several variants and comparing the resulting rankings with the baseline (Figure 5). The ordering is highly stable with respect to the magnitude of the weights: varying the dominant minimum-manning weight by $\pm 20\%$ leaves the ranking essentially unchanged (Spearman $\rho \approx 1.00$, with no change to the high-demand quartile), and removing or doubling the minor size weight still preserves a high correlation ($\rho = 0.88$ and 0.98 respectively) and an 84–89% overlap of the high-demand quartile. The conclusions therefore

do not hinge on the precise weight values. The one consequential modelling choice is the direction of the size component: reversing it, so that larger vessels are treated as more demanding, substantially alters the ranking ($\rho = 0.47$). This assumption—that smaller, less self-sufficient vessels place greater demand on the coordination centre—rests on operational judgement and is identified as the principal hypothesis to be examined in prospective validation.

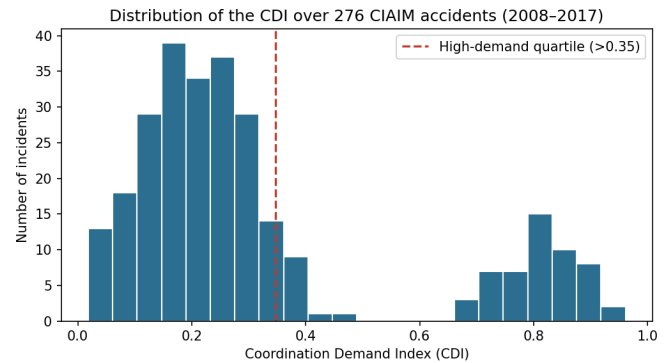


Figure 3: Distribution of the Coordination Demand Index (CDI) over the 276 CIAIM accidents (2008–2017), with the high-demand quartile threshold.

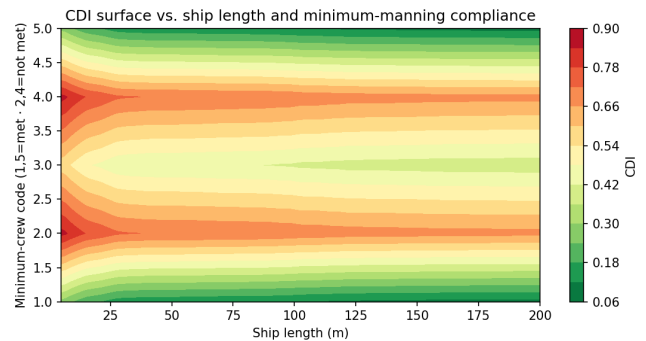


Figure 4: CDI surface as a function of ship length and minimum-manning compliance.

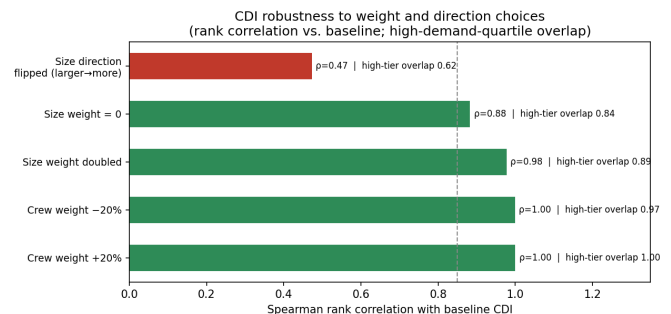


Figure 5: CDI robustness to weighting and direction choices: rank correlation with the baseline index and overlap of the high-demand quartile across variants.

3.3. Incident typology and screen triage.

The principal-component-and-*k*-means analysis reproduces the three archetypes identified for this dataset:

- **Cluster 1 – small and older vessels:** short length, older construction, minimum - manning requirement not met, highest accident risk.
- **Cluster 2 – large and modern vessels:** long length, recent construction, manning requirement met, accidents linked to environmental conditions.
- **Cluster 3 – fishing and recreational vessels:** small size, recreational or fishing use, predominant human factor and frequent operational errors.

Mapped onto the CDI, these archetypes define a three-tier screen-triage scheme (Figure 6). Cluster 2 corresponds to the low-demand (green) tier: such vessels retain on-board capacity for self-management, and their incidents are driven by external conditions rather than by manning or human factors. Clusters 1 and 3 correspond to the elevated-demand (amber/red) tiers and represent the “red points” that warrant heightened attention and verification. The scheme is conceived strictly as an aid to the controller’s judgement: it directs attention; it does not take decisions. Framed within the emergency lifecycle—initial failure, alert, coordination, and a critical decision taken on partial data—the *a priori* index supports the alert and coordination phases and the updated index supports the critical decision as information arrives.

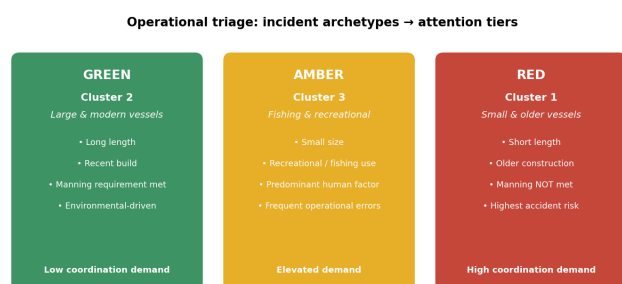


Figure 6: Three-tier screen-triage scheme: incident archetypes (clusters) mapped to attention tiers—green (Cluster 2), amber (Cluster 3), red (Cluster 1).

3.4. Operational context and the workload model.

The activity of the coordination network provides the operational backdrop. Over 2008–2016, Salvamento Marítimo coordinated between roughly 5,028 and 5,693 emergencies per year (annual reports), with recreational craft representing on average a little over half of the vessels involved, followed by fishing, merchant and other vessels including migrant craft (Figure 7). Activity is strongly concentrated geographically: in 2017 the centres of Algeciras and Almería alone coordinated close to 60% of all persons attended (Salvamento Marítimo, 2017).

Combining this volume with the staffing structure yields the workload model. With 135 controller-shifts available per

day across the network, an annual volume of the order of 5,260 emergencies corresponds to about 14 emergencies per day nationally, or approximately 0.11 emergencies per controller-shift on average—roughly one emergency every nine shifts. This deliberately low figure is the point of the model: measured as a raw count, the average load per controller is small. What makes the post demanding is not the number of emergencies but their complexity and their concentration—in a few centres, and, within the day, in the night shift, which is both the longest (ten hours against seven) and the one coinciding with the large share of night-time incidents identified by the CDI. This convergence is not merely inferential: a field study of 23 controllers (82% of the staff) across two Spanish Maritime Rescue Coordination Centres found a significant positive correlation between fatigue and mental workload that was most pronounced on the night shift and that depended on the operators’ usual sleep (Crestelo Moreno et al., 2023)—direct national evidence that the night shift is the system’s point of greatest cognitive vulnerability. The complexity-adjusted reading of the workload, rather than the raw count, is therefore the operationally meaningful one, and is precisely what the triage scheme is designed to surface.

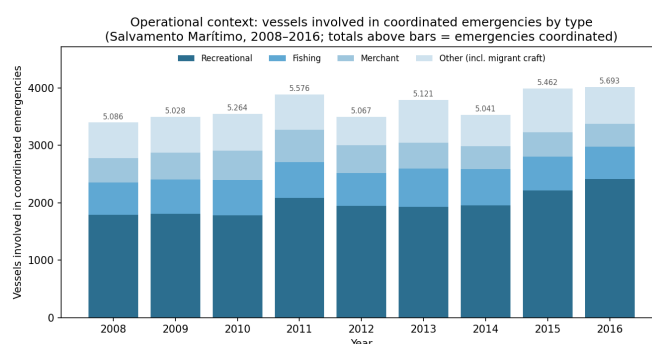


Figure 7: Operational context: vessels involved in coordinated emergencies by type, with annual emergency totals (Salvamento Marítimo, 2008–2016).

3.5. Relation to the international Vessel TRIAGE standard.

The term *triage* already has an established meaning in maritime emergencies. The Vessel TRIAGE method (Nordström et al., 2016), developed through a Finnish-led international cooperation and subsequently brought before the IMO Sub - Committee on Navigation, Communication and Search and Rescue, assesses and communicates the safety status of a vessel in distress using a matrix of materialised technical threat factors—such as flooding, loss of stability or fire—and a four-level categorisation: green, yellow, red and black. Its purpose is to give the distressed vessel and the SAR responders a shared understanding of whether the vessel can still provide a safe environment for the people on board.

The screen-triage scheme proposed here is complementary rather than competing, and the two must be distinguished to avoid terminological confusion (Table 1). Vessel TRIAGE looks outward, at the physical state of the casualty on scene; the CDI-based triage looks inward, at the coordination effort an incident

Table 1: Differentiation between the international Vessel TRIAGE standard and the CDI-based screen triage proposed here.

Dimension	Vessel TRIAGE (Nordström et al., 2016)	CDI-based screen triage (this work)
Object assessed	Physical safety status of the distressed vessel	Projected coordination demand at the MRCC
Intended users	Vessel master/crew and on-scene SAR units	Shore-based MRCC controllers
Categories	Four: green / yellow / red / black	Three: green / amber / red
Inputs	Materialised technical threat factors (flooding, loss of stability, fire, ...)	Early-observable attributes (manning, age, size, night, wind)
Temporal logic	Updated as threat factors evolve on scene	<i>A priori</i> at first alert → updated as information arrives
Status	Peer-reviewed; considered by the IMO NCSR Sub-Committee	Heuristic proposal, region-specific, controller-facing

is projected to demand of the shore-based controller. They operate at different points of the response and on different inputs. A mature decision-support environment could run both: Vessel TRIAGE to communicate the casualty's condition, and the CDI to help the controller allocate attention across the incidents under simultaneous coordination.

4. Conclusions.

This work has proposed an operational reading of maritime accident data for the Spanish SAR region, aimed not at explaining accidents after the fact but at supporting the controllers who coordinate the response to them. Three connected instruments have been developed from a single empirical base.

First, a Coordination Demand Index (CDI) translates the observable characteristics of an incident into a transparent estimate of the coordination effort it is likely to require. Its weights are anchored in the permutation-importance analysis of the accident records, which confirms the findings of earlier work for this region: compliance with the minimum safe-manning requirement is the dominant variable and visibility is effectively non-informative (Maceiras et al., 2021; Maceiras et al., 2024). Defined in two states—*a priori* from data available at the first alert, and updated as the emergency reveals the actual manning status—the index is built around the incomplete information that characterises real coordination rather than around idealised, fully observed inputs.

Second, the recurrent accident archetypes—large, modern, well-manned vessels at one extreme; small, older, undermanned vessels and human-factor-laden fishing and recreational craft at the other—have been mapped onto a three-tier screen-triage scheme. This turns a continuous index into something directly usable at the post: a visual flag that directs attention towards the incidents most likely to be demanding.

Third, a workload model has placed the index in operational context. Its central result is deliberately counter-intuitive: measured as a raw count, the average load is low—of the order of one emergency per controller every nine shifts. What makes the work demanding is not volume but the complexity of individual incidents and their concentration, both geographically, in a small number of centres, and temporally, in the long night shift. The CDI is precisely the instrument that makes this complexity, rather than the misleadingly low count, visible.

The analysis draws on accident records from 2008–2017, and it is fair to ask whether subsequent operational change has

overtaken it. The opposite is more likely. Over the past decade the coordination environment has been reshaped by a growing volume of real-time information—remotely piloted aircraft, automatic identification system feeds, smart buoys and automated alerting—much of which converges on the controller. Automating the collection of on-scene data does not lessen the cognitive task of consolidating it under time pressure; if anything, a richer data stream raises the risk of information overload unless the operator's interface includes effective layers of attention triage. The need that the CDI addresses therefore grows, rather than diminishes, with technological modernisation.

Several limitations should temper these conclusions and define the next steps. The CDI is proposed as a transparent heuristic, not as a validated predictor: its weights are informed by the importance of each variable for accident type, not optimised against measured coordination effort, and its component directions reflect operational judgement that should be tested empirically—most importantly the direction of the size component, which the sensitivity analysis (Section 3.2) identifies as the single choice to which the index ranking is most sensitive. The accident records on which it rests are investigated selectively by CIAIM on grounds of relevance, and therefore describe a particular slice of maritime activity rather than the full flow of emergencies. The fatigue argument, although supported by the structure of the shift system and the timing of incidents, is inferential within the present dataset—fatigue was not measured here—but it is consistent with field measurements of fatigue and mental workload in Spanish coordination centres that peak on the night shift (Crestelo Moreno et al., 2023). And the analysis is specific to the Spanish SAR region, where the influence of weather is attenuated by the navigation regime (Maceiras et al., 2024).

The natural continuation is prospective validation. The index should be tested against operational data that the coordination centres themselves generate—response times, the number of concurrent incidents, and outcomes—complemented by direct measurement of controller workload using established instruments such as the NASA-TLX (Hart and Staveland, 1988), which together would allow its weights and thresholds to be calibrated against measured demand rather than inferred from accident structure. Incorporating variables not present in the current records, such as crew experience, training and vessel maintenance (Maceiras et al., 2024), would further sharpen it. Beyond that lies the possibility of embedding the *a priori* index in the controller's display as the real-time “red-point” layer

described here, and of testing whether the same methodology transfers to other SAR regions. On the modelling side, the additive-linear form of the CDI assumes that its components substitute for one another; future iterations could relax this assumption through non-linear or multi-criteria formulations — fuzzy-logic inference, multi-criteria decision-making, or interdependence-aware methods such as DEMATEL— that represent interactions between the variables explicitly.

Ultimately, the contribution of this work is a way of seeing rather than a substitute for seeing. The instruments proposed here do not decide; they direct attention, surface complexity, and make explicit the demand that a controller already senses but that no raw statistic captures. In a domain where lives depend on judgements made quickly and on partial information, that is the proper role of technology: to serve the human operator, never to replace them.

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