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Communication Outweighs Competence: Determinants of Effective Engine-Department Response to Main Engine Failure in Severe Weather

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A B S T R A C T

This study examines the effectiveness of engine-department personnel management in responding to such failures, testing the relative contribution of four constructs: technical competence, communication, coordination, and preparedness. A quantitative survey was administered to 112 marine engineering officers enrolled at Banten Maritime Polytechnic, of whom 89.3% reported direct experience of engine failure at sea. The 60-item Likert instrument proved valid, with all items exceeding the critical value of 0.361, and highly reliable, with Cronbach's alpha of 0.948. All four constructs were perceived at a high level, with means between 3.83 and 4.10. Bivariate correlations with response effectiveness were uniformly strong, ranging from 0.849 to 0.940, and multiple regression explained 89.7% of the variance in effectiveness.

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INTRODUCTION

The main engine constitutes the single point upon which a vessel's propulsion, and therefore its capacity to maintain steerage and position, ultimately depends. Failure of this system is consequently among the most serious events that can occur at sea, and its severity is conditioned heavily by the circumstances in which it arises. Under settled conditions a disabled vessel may drift safely while repairs proceed; in storm conditions, with high seas and strong winds, the same failure removes the ship's ability to hold heading and exposes it to broaching, grounding, or collision. The reliability literature has documented this dependence in quantitative terms, with fault tree analysis of propulsion subsystems establishing that reliability falls sharply with accumulated running hours (Islam & Martin, 2025), and probabilistic assessment of blackout incidents demonstrating the propagation of individual component failures into total loss of power (Goksu et al., 2024).

Adverse weather compounds the problem through a second mechanism. Sui et al. (2022) demonstrated that adverse sea conditions materially degrade the propulsion and manoeuvring performance of low-powered cargo vessels, increasing the load imposed upon machinery at precisely the moment when reserve capacity is most needed. Severe weather therefore raises the probability of failure and the cost of failure simultaneously, and it does so while degrading the working conditions of the personnel who must respond.

Considerable effort has been directed at the technical dimension of this problem. Predictive and condition-based maintenance strategies have advanced substantially, with hybrid approaches combining reliability-centred and condition-based logic demonstrating cost-effective detection of incipient faults (Karatug et al., 2024), machine learning classifiers achieving fault detection accuracy approaching 99% on engine room simulator data (Kocak et al., 2023), and integrated frameworks employing Weibull analysis and Markov chains extending mean time to failure substantially (Budimir et al., 2025). Lazakis et al. (2018) combined fault tree and failure mode analysis with neural networks to predict the condition of critical main engine components.

The human dimension of the response has received markedly less attention. When a failure occurs notwithstanding the maintenance regime, the outcome depends upon the performance of the engine-department team: upon whether the fault is correctly diagnosed, whether the appropriate personnel are mobilised, whether the bridge is informed in terms that permit navigational decisions to be taken, and whether the team can execute under the physical and psychological stress that severe weather imposes. Research on non-technical skills in the maritime domain has developed principally with reference to the bridge, and its extension to the engine room remains comparatively recent. Nizar et al. (2022) developed an approach to measuring situation awareness in the engine control room as a component of engine resource management assessment, and Ishida et al. (2021) proposed a quantitative method for evaluating workload in engine-room resource management training. Wahl and Kongsvik (2018) reviewed crew resource management training in the maritime industry and identified persistent uncertainty regarding which components of such training account for its effects.

This uncertainty is consequential for the allocation of training resources. If technical competence is the principal determinant of effective response, investment should be directed towards technical instruction and certification; if communication and preparedness dominate, it should be directed towards protocol design and simulation. The question cannot be settled by bivariate association alone, since the constructs are conceptually and empirically intertwined, and a design capable of distinguishing unique from shared contribution is required.

Accordingly, this study examines the effectiveness of engine-department personnel management in responding to main engine failure during severe weather, and tests the relative contribution of technical competence, communication, coordination, and preparedness to that effectiveness. Two questions guide the enquiry: first, how do serving engineer officers perceive the level of each construct and its association with response effectiveness; and second, which constructs retain explanatory power when the others are controlled. The contribution of the study lies in confronting the divergence between bivariate and partial coefficients directly, and in drawing from that divergence an interpretation that is defensible in terms of the collinearity present in the data.

LITERATURE REVIEW

Machinery Failure and its Management

The engine room is a complex socio-technical system in which the main propulsion engine is supported by an extensive array of auxiliary systems, including compressed air, cooling, lubricating oil, fuel, and pumping subsystems. Failure in any of these can propagate to the main engine. Islam and Martin (2025) modelled the reliability of individual subsystems using failure running hour data collected from serving marine engineers and reported that the lubricating oil, freshwater cooling, scavenge, and fuel systems reach the point of exhausted reliability at markedly different operating intervals, with the overall propulsion engine reliability declining steeply thereafter. Goksu et al. (2024) applied fault tree analysis within a Bayesian network to assess the probability of blackout, quantifying the pathways by which local faults become total losses of power.

The maintenance literature has responded with increasingly sophisticated predictive methods. Karatug et al. (2024) proposed a hybrid strategy combining reliability-centred and condition-based maintenance, demonstrating detection of insufficient lubrication at low engine loads superior to prevailing practice and achieving this at low investment cost. Budimir et al. (2025) integrated Weibull reliability analysis, Markov chains, and data envelopment analysis across a dataset of 512 diesel engine components, and reported that targeted intervention in the degraded state reduced the proportion of failures in critical components substantially. Kocak et al. (2023) trained classifiers on engine room simulator data to achieve fault detection accuracy approaching 99%, while Lazakis et al. (2018) used neural networks to forecast exhaust gas temperatures as an indicator of main engine condition. Aslam et al. (2025) extended predictive maintenance to Internet of Things sensor deployments in the port context.

Two observations follow. First, technical means of anticipating failure are well developed and continue to improve. Second, and notwithstanding this, failures continue to occur, and the literature offers comparatively little guidance on the management of the response once they do. It is this residual, and by definition unanticipated, category of events that the present study addresses.

Non-Technical Skills in the Engine Department

Non-technical skills comprise the cognitive, social, and personal capacities that complement technical proficiency, and their significance in maritime operations has been established principally through accident analysis. Chauvin et al. (2013) found through Human Factors Analysis and Classification System coding that most collisions arise from decision errors, with preconditions including loss of situation awareness and deficits in communication. Shi et al. (2024) identified decision-making, cognitive capacity, situation awareness, and communication among the seafarer competencies most critical to accident prevention, and Kuzu (2026) determined through fuzzy DEMATEL analysis that self-awareness constitutes the most influential causal criterion within the network of non-technical skills. Veltsin et al. (2025) demonstrated that decision-making skills mediate the effects of training, leadership, and communication upon safety culture.

Application of this framework to the engine department is more recent. Nizar et al. (2022) developed an instrument for measuring situation awareness in the engine control room specifically as a component of engine resource management assessment, arguing that the bridge-derived measures could not be transferred without modification. Ishida et al. (2021) addressed the complementary problem of workload evaluation in engine-room resource management training through a quantitative approach. Kandemir et al. (2018) proposed a practical assessment technique for adopting simulators into marine engineering education, noting that learning outcomes depend heavily upon an assessment system aligned with the knowledge, understanding and proficiency that the competency standards specify.

Evidence on the effectiveness of resource management training itself is mixed. Wahl and Kongsvik (2018) reviewed crew resource management training in the maritime industry and found that, although such training is widely endorsed, the mechanisms through which it operates and the conditions under which it succeeds remain imperfectly specified. This echoes findings from adjacent high-risk domains: Gross et al. (2019) reviewed crew resource management training in healthcare and documented substantial heterogeneity in intervention design, training conditions, and evaluation approach, which impedes synthesis of effects. Praetorius et al. (2020) reached a similar conclusion in surveying maritime resource management training, identifying the sparseness of research linking such training to operational safety outcomes.

Communication, Coordination, and Preparedness

The three non-technical constructs examined here are distinguishable in principle but interdependent in practice. Communication concerns the transmission of information within the engine team and between the engine room and the bridge; coordination concerns the allocation of tasks and the synchronisation of action; preparedness concerns the anticipatory capability developed through drill, simulation, and procedural familiarity. Schmutz et al. (2019) established through systematic review and meta-analysis in healthcare that teamwork bears a robust positive relationship to performance, with the strength of that relationship increasing with task complexity. Salim et al. (2024) catalogued the factors influencing team communication in nuclear power plant emergency response, a setting whose combination of technical complexity and time pressure closely parallels engine room emergencies.

Preparedness has been examined principally through the evaluation of drills. Zhuge et al. (2024) assessed the effectiveness of emergency drills empirically and identified the organisational conditions under which they translate into capability. In the maritime setting, simulator-based training constitutes the principal vehicle for developing preparedness. Kim et al. (2021) traced the accelerating adoption of digital simulation technologies in maritime education, and Dewan et al. (2023) mapped the deployment of immersive and non-immersive simulators through systematic review, concluding that models evaluating efficacy from the learner's perspective remain a research priority.

Fatigue conditions all three constructs. Rajapakse and Emad (2023) documented that fatigue remains an unresolved contributor to casualties at sea notwithstanding long-standing regulation of rest hours. In severe weather, when watchkeeping demands intensify and rest is disrupted by vessel motion, the degradation of communication and decision-making attributable to fatigue is likely to be greatest at precisely the moment of highest demand. Fan et al. (2023) advanced a framework for incorporating seafarer psychological factors into maritime safety assessment on analogous grounds.

Research Gap

Three gaps emerge. First, the substantial literature on machinery reliability addresses the prevention of failure rather than the management of the response to it. Second, non-technical skills research in the maritime domain remains oriented towards the bridge, with engine-department applications comparatively few. Third, studies that do examine multiple determinants of team effectiveness typically report bivariate associations without testing unique contribution, leaving open the question of where marginal training investment should be directed. The present study addresses these gaps through a survey of serving engineer officers that tests four constructs simultaneously and interrogates the difference between their bivariate and partial coefficients.

METHODOLOGY

Design and Participants

A quantitative descriptive design was employed. Participants were 112 marine engineering officers enrolled in programmes at Banten Maritime Polytechnic, selected on the criterion of holding or having held a position within the engine department of a seagoing vessel. Their characteristics are reported in Table 1. The cohort is experienced rather than novice: 66.1% had served more than six years at sea, 82.2% held Engineer Officer Class III or Class IV certification, and 89.3% reported direct experience of main engine failure. A further 71.4% had attended engine emergency training. The sample is therefore well suited to the research question, since respondents were reporting upon events they had encountered rather than hypothetical scenarios.

Table 1. Characteristics of Respondents (N = 112).

Characteristic	Category	Frequency	Percentage (%)
Age	30 years or below	41	36.6
	31-40 years	50	44.6
	Above 40 years	21	18.8
Most recent rank	Chief Engineer	23	20.5
	First Engineer	3	2.7
	Second Engineer	41	36.6
	Third Engineer	24	21.4
	Fourth Engineer	7	6.3
	Engine Foreman	2	1.8
	Oiler	12	10.7
Sea service	Less than 1 year	4	3.6
	1-3 years	13	11.6
	4-6 years	21	18.8
	More than 6 years	74	66.1
Certification	Engineer Officer Class II	5	4.5
	Engineer Officer Class III	45	40.2
	Engineer Officer Class IV	47	42.0
	Engineer Officer Class V	15	13.4

Characteristic	Category	Frequency	Percentage (%)
Experienced engine failure	Yes	100	89.3
	No	12	10.7
Attended emergency training	Yes	80	71.4
	No	32	28.6

Instrument

Data were collected through a 60-item questionnaire measured on a five-point Likert scale, organised into four independent constructs and one dependent construct. Technical competence items addressed diagnostic knowledge, familiarity with machinery systems, and proficiency in repair procedures. Communication items addressed the clarity and timeliness of information exchange within the engine team and with the bridge. Coordination items addressed task allocation, role clarity, and the synchronisation of action. Preparedness items addressed familiarity with emergency procedures, participation in drills, and perceived readiness for unanticipated events. The dependent construct, effectiveness of failure response, addressed the speed, accuracy, and completeness with which main engine failures were addressed under severe weather conditions.

Validity and Reliability

Construct validity was assessed through Pearson item-total correlation. All 60 items returned coefficients exceeding the critical value of 0.361 at the applicable degrees of freedom, and all items were accordingly retained. Internal consistency was assessed through Cronbach's alpha, which returned a value of 0.948 for the full instrument, indicating a high degree of reliability. It should be noted that an alpha of this magnitude across 60 items, while confirming consistency, is also compatible with substantial item redundancy and with the inter-construct overlap that the regression analysis subsequently disclosed.

Analytical Procedure

Analysis proceeded in three stages. Descriptive statistics, comprising mean, standard deviation, skewness, and kurtosis, were computed for each construct in order to characterise the level and distribution of perceptions. Pearson correlation coefficients were then computed between each independent construct and the dependent construct in order to establish bivariate association. Finally, multiple linear regression was estimated with all four independent constructs entered simultaneously, in order to determine the unique contribution of each when the others are held constant. Model adequacy was assessed through the coefficient of determination, the F statistic for the joint significance of the predictors, the Durbin-Watson statistic for residual autocorrelation, and variance inflation factors for multicollinearity.

RESEARCH RESULT

Perceptions of the Four Constructs

Descriptive statistics for the four independent constructs are reported in Table 2 and displayed in panel (b) of Figure 1. All four returned means above 3.8 on the five-point scale, indicating that respondents perceived the level of each to be high. Coordination attained the highest mean at 4.10, followed by communication at 4.02, preparedness at 3.94, and technical competence at 3.83. Standard deviations were closely comparable across constructs, ranging from 0.67 to 0.70, indicating similar dispersion of opinion.

Table 2. Descriptive Statistics for the Four Independent Constructs

Construct	Mean	Std. deviation	Skewness	Kurtosis
Technical competence	3.83	0.68	-0.781	2.395
Communication	4.02	0.67	-1.149	3.646
Coordination	4.10	0.70	-1.287	3.724
Preparedness	3.94	0.69	-0.629	1.902

All four distributions exhibited negative skewness, ranging from -0.629 for preparedness to -1.287 for coordination, indicating a concentration of responses at the upper end of the scale. Kurtosis values ranged from 1.902 to 3.724. The pattern is consistent across constructs and indicates a generally favourable and reasonably uniform set of perceptions, with the least pronounced concentration occurring for preparedness, the construct on which respondents were least uniformly confident.

Bivariate Associations

Pearson correlations between each independent construct and the effectiveness of failure response are reported in Table 3. All four associations were positive, strong, and significant at $p < 0.01$.

Table 3. Pearson Correlations Between the Independent Constructs and Response Effectiveness

Independent construct	Pearson r	Sig. (p)	Interpretation
Technical competence	0.849	< 0.001	Strong, significant
Communication	0.940	< 0.001	Very strong, significant
Coordination	0.897	< 0.001	Very strong, significant
Preparedness	0.898	< 0.001	Very strong, significant

Communication returned the strongest association at r = 0.940, followed by preparedness at 0.898, coordination at 0.897, and technical competence at 0.849. Taken in isolation, these coefficients would support the conclusion that all four constructs contribute substantially to effective response, with communication foremost. The regression analysis, however, qualifies that conclusion materially.

Multiple Regression

Results of the multiple regression are reported in Table 4 and displayed alongside the correlations in panel (a) of Figure 1.

Table 4. Multiple Regression of Response Effectiveness on the Four Constructs

Predictor / Statistic	Standardised beta	Sig. (p)	Result
Technical competence	-0.058	0.478	Not significant (VIF > 5)
Communication	0.747	< 0.001	Significant
Coordination	0.014	0.886	Not significant (VIF > 5)
Preparedness	0.306	0.001	Significant
Coefficient of determination (R squared)	0.897	-	89.7% of variance explained
F statistic (joint significance)	233.385	< 0.001	Model significant
Durbin-Watson statistic	2.077	-	No material autocorrelation

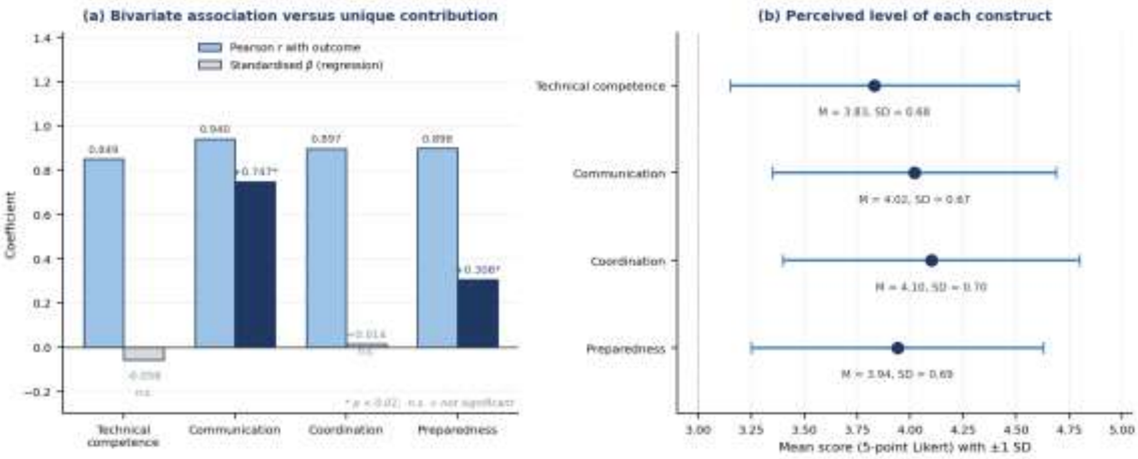

Figure 1. Bivariate Correlations Compared with Standardised Regression Coefficients, and Perceived Level of Each Construct.

The model as a whole performed strongly. The coefficient of determination was 0.897, indicating that the four constructs jointly account for 89.7% of the variance in response effectiveness, and the F statistic of 233.385 with $p < 0.001$ confirms their joint significance. The Durbin-Watson statistic of 2.077 falls within the conventional acceptable range, indicating no material autocorrelation in the residuals.

The partial coefficients, however, diverge sharply from the bivariate correlations. Communication retained a large and significant standardised coefficient of 0.747 at $p < 0.001$, and preparedness a smaller but significant coefficient of 0.306 at $p = 0.001$. Technical competence and coordination, by contrast, did not attain significance, returning coefficients of -0.058 at $p = 0.478$ and 0.014 at $p = 0.886$ respectively. The coefficient for technical competence is not merely non-significant but negative in sign, a reversal relative to its bivariate correlation of 0.849. Variance inflation factors for technical competence and coordination exceeded five, indicating that these constructs share a substantial proportion of their variance with the remaining predictors.

DISCUSSION

Interpreting the Divergence Between Correlation and Regression

The central analytical issue raised by these results is the discrepancy between the bivariate correlations, which are uniformly strong, and the partial coefficients, of which two are indistinguishable from zero and one has reversed sign. This pattern is characteristic of multicollinearity, and the variance inflation factors above five for the two non-significant predictors confirm that diagnosis directly. Kim (2019) sets out the consequences precisely: where predictors are highly intercorrelated, standard errors inflate, coefficient estimates become unstable, and signs may reverse without any implication that the underlying relationship is absent or negative.

The correct interpretation is therefore not that technical competence and coordination are unimportant to effective failure response. Such a conclusion would be untenable on its face, since it would imply that an engine department could respond effectively to main engine failure without technical proficiency. The tenable interpretation is that the variance these constructs share with communication and preparedness is sufficient that, once the latter are entered, no unique variance remains to be attributed to the former. In substantive terms, competence and coordination appear to operate through communication and preparedness rather than independently of them: a technically proficient engineer contributes to the outcome by communicating a correct diagnosis and by having rehearsed the response, and it is at the point of communication and rehearsal that the contribution becomes observable in the data.

This reading is consistent with the wider literature on non-technical skills. Veltsin et al. (2025) found through DEMATEL analysis that decision-making functions as a mediator channelling the effects of training, leadership, and communication upon safety culture, rather than as an independent determinant. Kuzu (2026) similarly positioned self-awareness as a causal criterion influencing other non-technical skills rather than acting in parallel with them. The structure identified here, in which two constructs mediate the influence of two others, follows the same logic. It also indicates a methodological requirement: the appropriate specification for this system is a mediation or structural model rather than a single-stage regression, and the present analysis should be read as establishing the existence of the mediation pattern rather than as estimating its parameters.

The Primacy of Communication

Communication emerged as the dominant predictor on both criteria, returning the highest bivariate correlation at 0.940 and much the largest partial coefficient at 0.747. The finding accords with a substantial body of evidence from adjacent domains. Chauvin et al. (2013) identified deficits in communication among the preconditions for collision at sea, and Shi et al. (2024) ranked communication among the competencies most critical to accident prevention. Salim et al. (2024) catalogued the factors governing team communication in nuclear power plant emergencies, a setting closely analogous to the engine room in its combination of technical complexity, time pressure, and consequence severity. Schmutz et al. (2019) established through meta-analysis that the association between teamwork and performance strengthens as task complexity increases, which implies that the premium upon communication should be greatest precisely in the severe-weather scenarios that this study addresses.

Two features of engine room work render communication particularly consequential. First, the acoustic environment is hostile, and in heavy weather the combination of noise, vibration, and vessel motion degrades the channel through which information must pass. Second, the engine room is not an autonomous unit: an engine failure requires the bridge to be informed promptly and in terms that permit navigational decisions, since the manoeuvring options available to the master depend upon the expected duration of the outage. A diagnosis that is technically correct but communicated late or ambiguously does not produce an effective outcome at the level of the vessel.

Preparedness and the Limits of Technical Instruction

Preparedness returned the second significant partial coefficient at 0.306, and also the lowest skewness among the four constructs, indicating that respondents were less uniformly confident on this dimension than on the others. Taken together these observations suggest that preparedness represents the construct with the greatest remaining scope for improvement within this cohort. Zhuge et al. (2024) established the conditions under which emergency drills translate into capability, and the maritime simulator literature offers well-developed vehicles for their delivery (Kim et al., 2021; Dewan et al., 2023). Ishida et al. (2021) and Nizar et al. (2022) demonstrated that engine-room resource management training can be evaluated quantitatively through workload and situation awareness measures, which would permit the effect of additional drill provision to be assessed rather than assumed.

The practical inference concerns the allocation of marginal training resource. The cohort surveyed is already technically well qualified, with 82.2% holding Class III or Class IV certification and two thirds having served more than six years. Among such a population the marginal return to further technical instruction is likely to be modest, whereas the return to structured communication protocol and emergency simulation, on the evidence presented here, is likely to be substantial. This does not license the reduction of technical training, whose contribution is embedded within the constructs that did attain significance; it indicates rather where additional resource should be directed. Wahl and Kongsvik (2018) and Praetorius et al. (2020) both observed that the maritime resource management literature has not established which components of such training account for its effects, and the present findings offer one specification of that question in the engine-department context.

Severe Weather as a Moderating Context

The severe-weather condition that frames this study is not incidental to the findings. Sui et al. (2022) demonstrated that adverse sea conditions degrade propulsion and manoeuvring performance and increase machinery loading, which raises both the probability of failure and the difficulty of recovering from it. Fatigue, whose contribution to casualties remains unresolved despite regulation (Rajapakse & Emad, 2023), is exacerbated by the disrupted rest that heavy weather produces. Fan et al. (2023) argued for the incorporation of seafarer psychological factors into safety assessment on precisely these grounds. The implication is that the constructs identified here as decisive, namely communication and preparedness, are also those most vulnerable to degradation under the conditions in which they are most needed, which strengthens rather than weakens the case for their deliberate reinforcement.

Limitations

Four limitations qualify these findings. First, all variables were measured through self-report from a single source at a single time, which exposes the estimates to common method bias; Podsakoff et al. (2024) document the pervasiveness and severity of this problem and the difficulty of remedying it post hoc. The uniformly high correlations observed here are consistent with, though not proof of, such inflation. Second, the multicollinearity documented above precludes reliable estimation of the unique contribution of technical competence and coordination, and the study can therefore establish the pattern of mediation but not its magnitude. Third, respondents were officers enrolled in shore-based education rather than personnel observed in service, and their reports concern recalled rather than contemporaneous events. Fourth, effectiveness was measured through perception rather than through objective indicators such as time to restore propulsion or incidence of secondary damage, and the correspondence between perceived and actual effectiveness was not established.

CONCLUSIONS AND RECOMMENDATIONS

This study examined the determinants of effective engine-department response to main engine failure during severe weather among 112 marine engineering officers. The instrument proved valid and highly reliable, with Cronbach's alpha of 0.948. All four constructs examined were perceived at a high level, with means between 3.83 and 4.10, and all correlated strongly with response effectiveness, with coefficients between 0.849 and 0.940. The four constructs jointly explained 89.7% of the variance in effectiveness. When entered simultaneously, however, only communication and preparedness retained significance, with standardised coefficients of 0.747 and 0.306 respectively, while technical competence and coordination did not, amid variance inflation factors above five. The study interprets this pattern as evidence that competence and coordination operate through communication and preparedness rather than independently of them.

Three recommendations follow. First, shipping companies and maritime training institutions should prioritise the development of structured communication protocols for engine-department emergencies, including standardised reporting formats for engine-to-bridge notification specifying the nature of the fault and the expected duration of the outage. Second, emergency preparedness should be strengthened through regular simulation of machinery failure under severe-weather conditions, with the effect of such provision evaluated through the workload and situation awareness measures that the engine-room resource management literature has developed. Third, technical training should be retained at its present level rather than expanded, on the ground that its contribution is already transmitted through the constructs that proved decisive and that the cohort is technically well qualified.

ADVANCED RESEARCH

Four directions for further enquiry follow directly from the limitations identified. First, the mediation structure hypothesised here should be tested explicitly through structural equation modelling, which would permit the indirect effects of competence and coordination through communication and preparedness to be estimated rather than inferred. Second, the measurement of response effectiveness should be extended beyond self-report to objective indicators, including time to restore propulsion, incidence of secondary damage, and assessments recorded by superintendents or classification surveyors. Third, procedural remedies for common method bias, including temporal separation of predictor and criterion measurement and the collection of criterion data from a second source, should be incorporated at the design stage. Fourth, the study should be replicated on a sample of officers observed in service rather than in shore-based education, and ideally across vessel types and trading patterns with differing exposure to severe weather.

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