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# Artificial intelligence capability as a mediator between human resource management, logistics coordination, and flood response performance in Malaysia

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## Abstract

Flood response requires coordinated organizational resources and appropriate technological capabilities. This study examined associations among human resource management (HRM), logistics coordination (LC), artificial intelligence capability (AIC), and flood response performance (FRP) among respondents involved in Malaysian flood-response activities. A cross-sectional survey conducted between September 2025 and February 2026 provided 593 responses. Questionnaire items were developed from a review of relevant literature. The revised analysis used observed mean composite scores, standardized ordinary least squares regression, and 3,000 bootstrap resamples to estimate direct and indirect associations. HRM and LC were positively associated with AIC, while AIC and LC were positively associated with FRP. Significant indirect associations through AIC were identified for HRM and LC. The direct HRM–FRP association was nonsignificant under bootstrap inference but significant under conventional regression inference, indicating sensitivity to the uncertainty estimation method. The findings provide preliminary evidence concerning organizational capabilities and perceived flood response performance. However, the cross-sectional design, purposive sampling, and absence of independent validation limit causal interpretation and generalizability.

***Keywords:*** Artificial intelligence capability; Disaster response; Human resource management; Sustainable Development Goal 16

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## 1. Introduction

Flooding is one of the most destructive phenomena on Earth, impacting millions of people every year and causing large-scale economic, environmental, and social devastation. According to the Intergovernmental Panel on Climate Change, climate warming has led to more frequent and more intense extreme weather occurrences, causing flash floods, riverine floods, and coastal inundation to become more common in many global locations. Developing countries are especially susceptible due to rapid urbanization, lack of drainage infrastructure, growing populations in flood-prone

areas, and lack of disaster preparedness. Floods remain an ongoing threat to human lives, public infrastructure, economic productivity, and environmental sustainability in Southeast Asia. Therefore, flood disaster management has become an increasingly important research priority. This urgency was further demonstrated by the severe flash floods that affected several districts in Nepal on August 26, 2026.[1]

Malaysia experiences seasonal monsoon floods almost every year, with major flooding events in states such as Kelantan, Pahang, Johor, Selangor, and Terengganu. Such disasters frequently disrupt transportation, communication, health, education, and business services, requiring large-scale humanitarian assistance from multiple stakeholders. The growing complexity of flood disasters has transformed emergency response from a purely operational activity to a strategic organizational capability that requires strong coordination among government agencies, non-governmental organizations (NGOs), local communities, volunteers, and private-sector organizations. Thus, enhancing flood response performance (FRP) has become one of the main objectives of disaster management policies worldwide.[2-4]

Flood response performance is the capacity of emergency organizations to provide timely, coordinated, efficient, and effective humanitarian assistance before, during, and immediately after flood disasters. Effective disaster response organizations share information rapidly, deploy resources efficiently, communicate effectively, maintain accurate situational awareness, coordinate logistics, and have well-trained emergency personnel. A weak response, by contrast, often results in delayed evacuations, scarce relief supplies, duplicated relief efforts, inefficient resource utilization, and increased human suffering. Previous research in humanitarian logistics has clearly demonstrated that organizational capabilities are an important determinant of effectiveness in disaster response, especially in uncertain, resource-constrained, and dynamic operational contexts.[2,5,6]

Among the organizational capabilities that contribute to successful disaster response, human resource management (HRM) has emerged as one of the most important factors for organizational readiness. Disaster response organizations operating under extreme pressure require technical knowledge, operational expertise, leadership skills, and psychological resilience to function effectively. Organizations can develop a workforce capable of adapting to the rapidly changing disaster environment through strategic HRM practices such as recruitment, competency development, emergency training, knowledge management, performance evaluation, and employee empowerment. Continuous disaster preparedness training improves employees' ability to make timely operational decisions, coordinate interagency activities, and respond effectively to emergencies. Recent evidence from Malaysia has revealed that organizations with more robust HRM practices have higher organizational resilience, better crisis management capability, and higher operational performance during emergencies.[7-9] These studies further illustrate that HRM has a beneficial effect on humanitarian operations performance during flood response, emphasizing the importance of strategic workforce development in disaster management.

Another key capability for successful flood response is logistics coordination (LC), in addition to human resources. Humanitarian logistics includes planning, procurement, transportation, storage, and distribution of emergency supplies, equipment, medical resources, and personnel to disaster-affected communities. During flood emergencies, many organizations have to coordinate across different geographical locations, often under severe time constraints and uncertain information. Efficient LC improves resource visibility, minimizes duplicated relief efforts, improves stakeholder communication, and enables rapid delivery of humanitarian assistance. Poor coordination, by contrast, often leads to congestion, slow aid delivery, poor inventory management, and reduced operational efficiency. Humanitarian logistics scholars have repeatedly emphasized that coordinated logistics systems are among the strongest predictors of disaster response performance because they enhance organizational efficiency as well as interorganizational collaboration.[2,6,10] Empirical evidence from Malaysian flood response organizations also confirms that LC can greatly improve the performance of humanitarian operations.[2,6,10]

While HRM and LC have been shown to have positive effects on disaster response independently, the growing complexity of modern-day disasters has created new demands for advanced technological capabilities that can aid organizational decision-making. Today's emergency managers are bombarded with huge volumes of information from weather forecasts, satellite images, social media, Internet of Things devices, unmanned aerial vehicles, geographic information systems (GIS), and field reports. Traditional decision-making paradigms are often not able to integrate these heterogeneous data sources in time to support real-time operational decisions. Thus, artificial intelligence (AI) has become one of the most essential transformational technologies for disaster management. It enables organizations to process large and complex datasets, predict disaster impacts, optimize resource allocation, identify priority rescue locations, and enable

data-driven decision-making. Recent reviews indicate that AI significantly boosts situational awareness, demand forecasting, evacuation planning, and humanitarian logistics optimization, thereby improving disaster response effectiveness and minimizing operational uncertainty.[8]

Artificial intelligence is becoming an organizational capability that relies on skilled employees, effective knowledge sharing, coordinated operational processes, and strong institutional support. In general, organizations with competent personnel and well-coordinated logistics systems are better positioned to implement AI technologies successfully, as these foundational capabilities support data quality, organizational learning, technology adoption, and collaborative decision-making. Therefore, from a resource-based view (RBV) and dynamic capabilities theory perspective, AI capability can be conceived as an organizational higher-order competency that converts current human and operational resources into superior organizational performance.[11,12] This suggests that investment in HRM and LC may affect FRP indirectly through strengthening AI capability, rather than directly improving operations.

Artificial intelligence is rapidly changing the way we manage complex organizational processes in both the public and private sectors. AI encompasses a wide range of technologies including machine learning, deep learning, computer vision, natural language processing, big data analytics, and predictive modeling that assist organizations to analyze large volumes of structured and unstructured data, generate real-time insights, and make evidence-based decisions.[13,14] AI is increasingly applied to disaster management because emergency response operations require organizations to simultaneously process heterogeneous information from weather forecasts, satellite images, unmanned aerial vehicles, Internet of Things sensors, social media, GIS, and field personnel. These data are highly diverse, but traditional decision-making methods cannot merge them quickly enough to make timely interventions during a flood emergency.

Recent studies demonstrate that AI substantially improves disaster management, such as flood prediction, evacuation planning, resource allocation, damage assessment, and logistics optimization, improving preparedness, response, and recovery. Machine learning algorithms are becoming more effective in predicting flood occurrence with higher accuracy than traditional statistical models, and deep learning techniques enable near-instantaneous flood mapping with satellite imagery and remote sensing data.[15] AI-enabled decision support systems have also improved emergency resource allocation by identifying optimal transportation routes, predicting humanitarian supply demand, and prioritizing rescue operations according to risk severity.[16,17] Recent advances in generative AI have expanded the scope of disaster management through intelligent assistants that can synthesize operational information, support emergency planning, and improve communication between disaster response organizations.[13,18]

Nevertheless, successful AI adoption is more than merely gaining new technologies; it is also building organizational capability that enables organizations to effectively deploy, integrate, and use AI in operational decision-making. Researchers argue that AI capability is an organizational competency that encompasses technological infrastructure, skilled personnel, data management capabilities, organizational learning, and collaborative processes that generate strategic value.[19] This perspective is in accordance with RBV, which asserts that sustained organizational success is built upon precious, uncommon, distinctive, and unique resources that are effectively combined into organizational capabilities.[11] Likewise, dynamic capabilities theory argues that firms need to constantly recombine, reconfigure, and renew internal and external resources to respond quickly to dynamically changing surroundings.[12] Therefore, AI capability in flood response operations is a higher-order organizational competence that enables emergency groups to leverage human expertise and coordinated logistics into a faster, better-informed, and more effective disaster response.

Therefore, this study enhances disaster management literature by illustrating how artificial intelligence capability (AIC) serves as a strategic tool that converts HRM and LC into enhanced FRP, fostering the creation of more resilient and technology-driven disaster response systems in Malaysia. The study corresponds with the United Nations Sustainable Development Goals (SDGs), specifically SDG 9 (Industry, Innovation and Infrastructure) by fostering AI-driven innovation in disaster management, SDG 11 (Sustainable Cities and Communities) by bolstering community resilience and disaster preparedness, and SDG 13 (Climate Action) by enhancing adaptive capacities and optimizing flood response strategies for climate-related disasters. The results are expected to contribute to achieving SDG 9, SDG 11, and SDG 13 by providing empirical evidence on improving disaster resilience, increasing the efficiency of emergency response, and promoting sustainable flood risk management in Malaysia through the integration of HRM, LC, and AIC.

## 2. Methods

This study used a quantitative cross-sectional survey to

examine hypothesized associations among HRM, LC, AIC, and FRP among respondents involved in Malaysian flood-response activities. The revised analysis employed regression-based path analysis of observed composite scores. Each construct was represented by the mean of its retained questionnaire items, and standardized ordinary least squares (OLS) regression was used to estimate the proposed relationships. Bootstrapping was performed to quantify uncertainty in the direct and indirect estimates. This approach evaluates associations among observed composite scores rather than estimating a latent-variable partial least squares structural equation modeling (PLS-SEM) model. Consequently, the results do not establish causal relationships or temporal ordering.[20]

### 2.1. Data and sample collection

**Figure 1** illustrates the monthly flood context in Malaysia during the survey period of September 2025–February 2026. The number of flood incidents recorded was highest in November 2025 (68), and subsequently went down to 14 in February 2026. Monthly flood data are derived from the National Disaster Management Agency (NADMA), National Disaster Command Center Monthly Disaster Reports, September 2025–February 2026; fundamental data are sourced from the Disaster Management Secretariat, Malaysia Civil Defense Force (APM).

A systematic questionnaire was created based on the existing research to ensure the validity and reliability of the measurement constructs. There are five components in the instrument, which are demographic data, HRM, LC, AIC, and FRP. All assessment items were evaluated on a five-point Likert scale, with a scale of 1 (strongly disagree) to 5 (strongly agree). For the revised analysis, HRM and LC were represented by eight items each, AIC by 16 items, and FRP by 15 items following the removal of questionnaire item F1.11. The original indicator label Y1.16 was retained. The survey instrument was evaluated by scholarly authorities and disaster management professionals prior to the main survey to ensure that it was appropriate for the Malaysian flood response scenario, content validity, and clarity. The study recruited individuals with relevant disaster management experience from government agencies and NGOs in Malaysia using purposive sampling. The unit of analysis was the individual respondent, whose questionnaire responses were used to construct the study variables. Government agencies such as the APM and NGOs such as MERCY Malaysia, Malaysian Red Crescent, Islamic Relief Malaysia, and Humanitarian Care Malaysia were the selected agencies involved in humanitarian efforts. The required sample size was estimated using G*Power (version 3.1.9.7, Heinrich Heine University Düsseldorf, Germany), configured with two predictors, an effect size of 0.15, a statistical power of 0.95, and a significance threshold of 0.05. Researchers stipulated that a sample size of 129 participants was necessary.[21] Data were collected through a cross-sectional survey from September 2025 to February 2026. Multiple flooding incidents were observed throughout Malaysia during the brief La Niña period.[22] The data collection period aligns

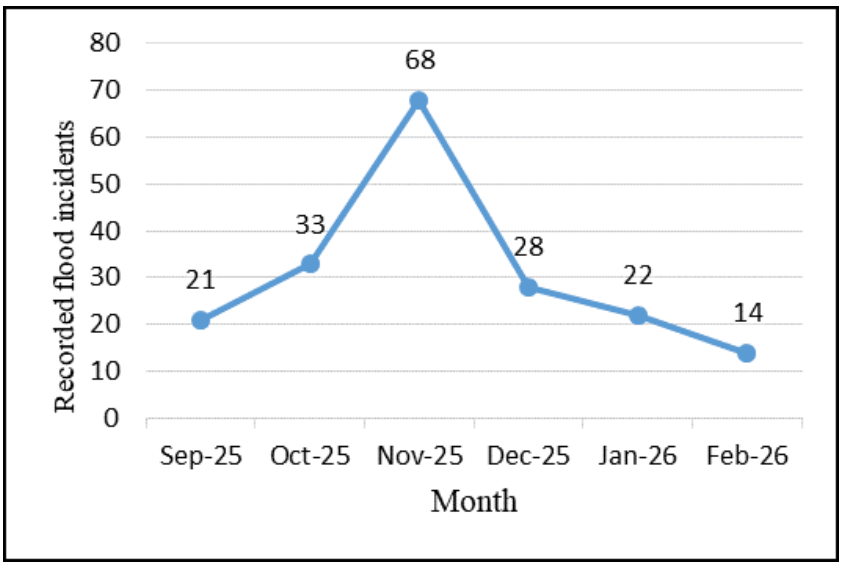



**Figure 1.** Monthly flood incidents in Malaysia during the questionnaire data collection period from September 2025 to February 2026. The number of incidents rose from 21 in September to 33 in October, peaking at 68 in November, and subsequently decreased to 28 in December, 22 in January, and 14 in February.

with this observation. The revised dataset contained 593 complete responses for the 47 retained measurement items and was analyzed in Python (version 3.11.9, Python Software Foundation, United States). Respondents were from a wide range of humanitarian and emergency response organizations operating in Malaysia. The largest proportion of respondents came from Humanitarian Care Malaysia (25.8%), followed by Islamic Relief Malaysia (23.1%), MERCY Malaysia (22.1%), and Malaysian Red Crescent (16.2%). The APM was the most represented government agency, with respondents from the combined central, south, and east zones (9.1%), followed by the Fire and Rescue Department Malaysia (1.7%) and Land Public Transport Agency (2.0%). The statistical distribution indicates that the study succeeded in obtaining views from the two major humanitarian NGOs and the key government agencies involved in flood response operations in Malaysia. These percentages describe the recruited sample and do not establish population representativeness. State-level respondent locations were not collected.

### 2.2. Data analysis

Data were analyzed in Python using regression-based path analysis of observed composite scores. Each construct was represented by the mean of its retained questionnaire items. The revised dataset comprised 593 complete responses for 47 indicators, with all indicator values within the five-point response scale. F1.11 was excluded following identification of its low item–construct correlation in the earlier analysis. This constituted a post hoc measurement revision; no additional indicators were removed.

Internal consistency was assessed using Cronbach's alpha. Pearson correlations between individual items and their corresponding construct means were calculated as descriptive indicator diagnostics. Composite reliability (CR)-style and average variance extracted (AVE)-style summaries were derived from these correlations, drawing on conventional reliability and convergent-validity concepts.[21,23] However, these summaries were not obtained from a fitted latent-variable measurement model and should not be interpreted as equivalent to PLS-SEM measurement estimates. Because each item contributed to its corresponding construct mean, the item–construct correlations also contained a part–whole relationship.

Construct overlap was examined using Pearson correlations, a supplementary Fornell–Larcker-style comparison,[24] and the heterotrait–monotrait ratio of correlations (HTMT).[25] The supplementary comparison contrasted square root AVE-style diagnostics with interconstruct correlations. HTMT was calculated using absolute item correlations and evaluated against thresholds of 0.85 and 0.90.[25] Both thresholds were reported to show the assessment sensitivity. Bootstrap confidence intervals (CIs) for HTMT were not calculated; therefore, interpretation was restricted to point estimates.

Two standardized OLS regression equations were estimated. AIC was regressed on HRM and LC, while FRP was regressed on HRM, LC, and AIC. Predictor collinearity was assessed using variance inflation factors (VIF). The equations were summarized using $R^2$, adjusted $R^2$, and incremental $f^2$ values. These statistics describe explanatory performance within the analyzed sample and do not establish out-of-sample predictive accuracy. Indirect associations were calculated as products of the relevant regression coefficients. Following the general use of bootstrap inference for indirect relationships, uncertainty was assessed using 3,000 respondent-level bootstrap resamples, with composite scores re-standardized within each resample.[21] 95% percentile CIs were calculated, and two-sided normal-approximation $p$-values were obtained from coefficient-to-bootstrap-standard-error ratios. The random seed was 20261002. Conventional OLS standard errors and significance tests were reported separately to examine sensitivity to the inference method. Both analyses used the same dataset and did not constitute independent validation. Given the cross-sectional design, direct and indirect estimates were interpreted as statistical associations rather than causal effects.

## 3. Results

Table 1 presents internal consistency and composite-score measurement diagnostics for the retained indicators. Cronbach's alpha ranged from 0.900 to 0.942, exceeding the conventional internal-consistency benchmark of 0.70.[21] Item–construct correlations ranged from 0.757 to 0.798 for HRM, 0.741 to 0.790 for LC, 0.574 to 0.798 for AIC, and 0.682 to 0.755 for FRP. The revised FRP scale comprised 15 items following F1.11 removal. CR-style diagnostics ranged from 0.919 to 0.949, while AVE-style diagnostics were 0.599 for HRM, 0.587 for LC, 0.538 for AIC, and 0.521 for FRP. In conventional reflective measurement assessment, CR above 0.70 and AVE above 0.50 are commonly used benchmarks.[21,24] However, the present diagnostics were calculated from correlations between items and their corresponding mean composite scores, rather than from a fitted latent-variable measurement model. Therefore, meeting these numerical benchmarks does not establish equivalent evidence of latent-variable reliability or convergent validity.

Following F1.11 removal, FRP had a Cronbach's alpha of 0.934, a CR-style diagnostic of 0.942, and an AVE-style diagnostic of 0.521. These values exceeded those reported

**Table 1. Internal consistency and composite-score measurement diagnostics**

| Construct | Items | Cronbach's α | CR-style diagnostic | AVE-style diagnostic | Minimum item–construct correlation | Maximum item–construct correlation |
|---|---|---|---|---|---|---|
| HRM | 8 | 0.904 | 0.923 | 0.599 | 0.757 | 0.798 |
| LC | 8 | 0.900 | 0.919 | 0.587 | 0.741 | 0.790 |
| AIC | 16 | 0.942 | 0.949 | 0.538 | 0.574 | 0.798 |
| FRP | 15 | 0.934 | 0.942 | 0.521 | 0.682 | 0.755 |

Notes: Item–construct correlations were calculated against mean composite scores containing the respective items. CR-style and AVE-style diagnostics were derived from these correlations and are not estimates from a fitted latent-variable measurement model. F1.11 was excluded; Y1.16 was retained.
Abbreviations: AIC: Artificial intelligence capability; AVE: Average variance extracted; CR: Composite reliability; FRP: Flood response performance; HRM: Human resource management; LC: Logistics coordination.

for the previous 16-item FRP scale. Nevertheless, AIC retained comparatively weak item–construct correlations for questionnaire items A3.15 (0.616) and A3.16 (0.574). Measurement guidance recommends considering indicator strength alongside theoretical relevance and construct coverage.[21] The findings consequently support improved FRP measurement diagnostics while indicating that further assessment of indicator quality remains necessary.

Table 2 presents a supplementary comparison of square root AVE-style diagnostics with correlations among the observed composite scores. The LC–AIC correlation of 0.794 exceeded the corresponding diagonal values for LC (0.766) and AIC (0.734). The AIC–FRP correlation of 0.805 also exceeded the diagonal values for AIC (0.734) and FRP (0.722). In addition, the LC–FRP correlation of 0.760 exceeded the FRP diagonal value. Therefore, the comparison indicates substantial overlap among LC, AIC, and FRP. Because the AVE-style diagnostics were derived from item–mean correlations, this table is descriptive and should not be treated as a formal latent-variable discriminant-validity assessment.

The complete HTMT results ranged from 0.723 to 0.858 (Table 3). All six construct pairs were below 0.90, but LC–AIC (0.858) and AIC–FRP (0.855) exceeded 0.85. Thus, the point estimates met the more permissive criterion but did not consistently meet the stricter criterion. No bootstrap CIs for HTMT were available. Therefore, the relationships involving LC, AIC, and FRP should be interpreted with caution, and satisfactory discriminant validity should not be claimed without qualification.[24]

**Table 2. Supplementary Fornell–Larcker-style comparison for observed composite scores**

| Construct | HRM | LC | AIC | FRP |
|---|---|---|---|---|
| HRM | 0.774 | 0.748 | 0.711 | 0.663 |
| LC | 0.748 | 0.766 | 0.794 | 0.760 |
| AIC | 0.711 | 0.794 | 0.734 | 0.805 |
| FRP | 0.663 | 0.76 | 0.805 | 0.722 |

Notes: Diagonal values are square roots of AVE-style diagnostics calculated from item–mean correlations. Off-diagonal values are Pearson correlations among construct means. This comparison is supplementary and does not establish latent-variable discriminant validity.
Abbreviations: AIC: Artificial intelligence capability; AVE: Average variance extracted; FRP: Flood response performance; HRM: Human resource management; LC: Logistics coordination.

**Table 3. Complete HTMT results**

| Construct pair | HTMT | Below 0.90 |
|---|---|---|
| HRM–LC | 0.829 | Yes |
| HRM–AIC | 0.769 | Yes |
| HRM–FRP | 0.723 | Yes |
| LC–AIC | 0.858 | Yes |
| LC–FRP | 0.829 | Yes |
| AIC–FRP | 0.855 | Yes |

Abbreviations: AIC: Artificial intelligence capability; FRP: Flood response performance; HRM: Human resource management; HTMT: Heterotrait–monotrait ratio of correlations; LC: Logistics coordination.

The reliability of the indicators of the measurement model was evaluated using the outer loadings of all measurement items. Figure 2 illustrates Pearson item–construct correlations for the 47 retained indicators of HRM, LC, AIC, and FRP. F1.11 was excluded; Y1.16 represents the original code for the final FRP indicator. Correlations were calculated against construct means containing the respective items. Colors distinguish unrounded values below and at or above 0.70. Vertical lines at 0.60 and 0.70 provide visual reference points. These correlations are descriptive diagnostics rather than PLS-SEM outer loadings. Researchers state that the ideal indicator loadings are greater than 0.70 and that loadings between 0.40 and 0.70 may be kept if the constructs exhibit good composite reliability and convergent validity.[21]

### 3.1. Regression-based path analysis

Table 4 reports standardized regression coefficients with bootstrap uncertainty estimates. The AIC equation explained 66.2% of the variance in observed AIC scores ($R^2$ = 0.662; adjusted $R^2$ = 0.661). HRM was positively associated with AIC (β = 0.266, 95% CI [0.179, 0.352], $p$ < 0.001), as was LC (β = 0.595, 95% CI [0.511, 0.671], $p$ < 0.001). The FRP equation explained 69.0% of the variance in observed FRP scores ($R^2$ = 0.690; adjusted $R^2$ = 0.688). AIC had a significant positive association with FRP (β = 0.521, 95% CI [0.402, 0.630], $p$ < 0.001). LC also retained a significant positive association with FRP (β = 0.289,

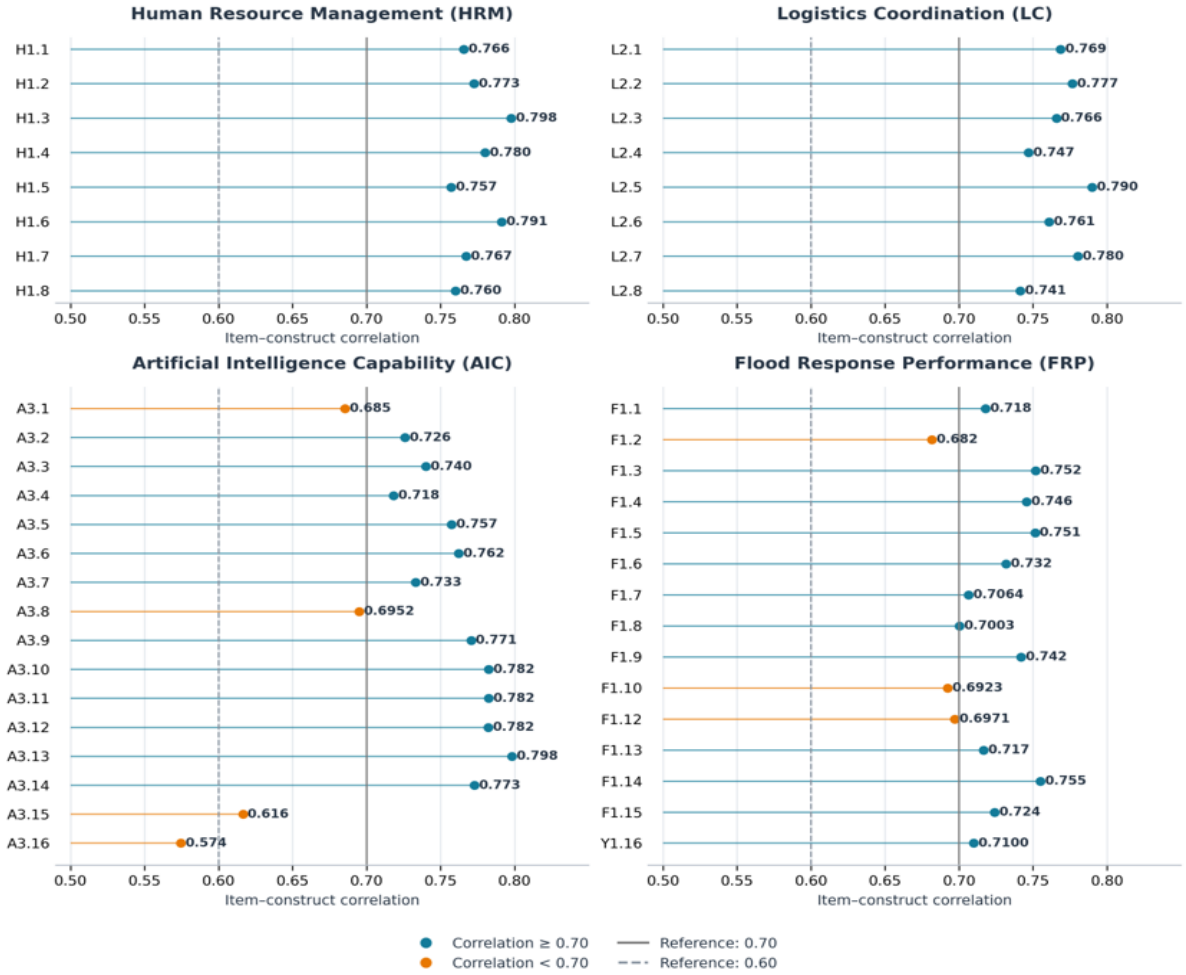



**Figure 2.** Item–construct correlations for HRM, LC, AIC, and FRP. F1.11 was excluded, while all other indicators were retained; Y1.16 is an FRP indicator. Each item contributes to its corresponding construct mean. Colors indicate unrounded correlations; values near 0.70 are shown up to four decimal places. The lines at 0.60 and 0.70 are visual guides rather than validated cutoffs. These values represent descriptive correlations rather than PLS-SEM outer loadings.

Abbreviations: AIC: Artificial intelligence capability; FRP: Flood response performance; HRM: Human resource management; LC: Logistics coordination; PLS-SEM: Partial least squares structural equation modeling.

95% CI [0.167, 0.408], $p < 0.001$). The direct HRM–FRP association was not significant under bootstrap inference (β = 0.075, 95% CI [−0.027, 0.193], $p = 0.180$). However, conventional OLS inference yielded $p = 0.037$ for the same coefficient, indicating sensitivity to the method used to estimate uncertainty. Predictor VIF values ranged from 2.271 to 3.318. LC's VIF in the FRP equation exceeded 3.0 but remained below 5.0, warranting attention alongside the observed construct overlap. The $R^2$ values describe explanatory performance within the analyzed sample and do not establish predictive accuracy in independent organizations or flood events.

The indirect HRM–AIC–FRP association was positive and significant (β = 0.139, 95% CI [0.089, 0.195], $p < 0.001$) (Table 5). Under bootstrap inference, this occurred alongside a nonsignificant direct HRM–FRP association, producing a pattern consistent with indirect-only mediation (Figure 3). However, the direct association was significant under conventional OLS inference. Therefore, the mediation classification is sensitive to the inference method and should not be described as definitive full mediation. The indirect LC–AIC–FRP association was also positive and significant (β = 0.310, 95% CI [0.231, 0.388], $p < 0.001$). Along with the significant positive direct LC–FRP association, this pattern is consistent with complementary partial mediation. These indirect associations were estimated from cross-sectional observed composite scores and do not establish temporal or causal mechanisms. No interaction terms were included, and moderation was not tested.

## 4. Discussion

The revised analysis identified positive associations between organizational resources, perceived AI capability, and perceived FRP. AIC had a substantial positive direct association with FRP after adjustment for HRM and LC (β = 0.521, 95% CI [0.402, 0.630], $p < 0.001$), consistent with Table 4. LC was associated with FRP directly and indirectly through AIC. The direct HRM–FRP association was sensitive to the inference method, while the indirect association through AIC was significant. These findings are consistent with the proposed intermediary association pattern but do not establish a causal mechanism. Alternative explanations include broader organizational maturity, shared response tendencies, and overlapping measurement content. The study extends the organizational capability discussion in Malaysian flood-response research, while leaving temporal direction and operational relevance unaddressed.[26,27]

Removing F1.11 improved the FRP measurement diagnostics, but the revision did not resolve overlap among LC, AIC, and FRP. Furthermore, the new dataset produced different HRM results; therefore, the changes cannot be attributed solely to removal of the FRP item. Consequently, the revised findings should be interpreted as results from the newly supplied dataset rather than as a controlled comparison isolating the consequences of deleting F1.11.

The findings also contribute directly to achieving SDG 16 (Peace, Justice and Strong Institutions), especially Target 16.6, which advocates for the development of effective, accountable, and transparent institutions, and Target 16.7, which advocates for responsive, inclusive, participatory, and representative decision-making.[28] Institutional capacity, interagency collaboration, and evidence-based decisions are more critical than physical resources for

**Table 4. Standardized regression associations with bootstrap inference**

| Hypothesis | Association | β | Bootstrap SE | Bootstrap ratio | *p* | Bootstrap 95% CI | $f^2$ | Decision* |
|---|---|---|---|---|---|---|---|---|
| H1 | HRM → AIC | 0.266 | 0.044 | 6.036 | <0.001 | [0.179, 0.352] | 0.092 | Supported |
| H2 | LC → AIC | 0.595 | 0.041 | 14.395 | <0.001 | [0.511, 0.671] | 0.461 | Supported |
| H3 | AIC → FRP | 0.521 | 0.058 | 8.987 | <0.001 | [0.402, 0.630] | 0.296 | Supported |
| H4 | HRM → FRP | 0.075 | 0.056 | 1.341 | 0.180 | [−0.027, 0.193] | 0.007 | Not supported* |
| H5 | LC → FRP | 0.289 | 0.061 | 4.712 | <0.001 | [0.167, 0.408] | 0.081 | Supported |

Notes: Coefficients (β) were estimated using standardized OLS regression of observed mean composite scores. Bootstrap results use 3,000 resamples and percentile CIs. The bootstrap ratio is β divided by its bootstrap standard error; *p*-values use a two-sided normal approximation. $f^2$ represents incremental explained variance. AIC $R^2 = 0.662$; FRP $R^2 = 0.690$. *Decisions use bootstrap inference; H4 was significant under conventional OLS inference ($p = 0.037$).

Abbreviations: AIC: Artificial intelligence capability; CI: Confidence interval; FRP: Flood response performance; HRM: Human resource management; LC: Logistics coordination; OLS: Ordinary least squares; SE: Standard error.

**Table 5. Bootstrap estimates of indirect associations through AIC**

| Hypothesis | Indirect association | β | Bootstrap SE | Bootstrap ratio | *p* | Bootstrap 95% CI | Interpretation |
|---|---|---|---|---|---|---|---|
| H6 | HRM → AIC → FRP | 0.139 | 0.028 | 5.041 | <0.001 | [0.089, 0.195] | Significant indirect association; classification sensitive to direct-path inference |
| H7 | LC → AIC → FRP | 0.310 | 0.040 | 7.840 | <0.001 | [0.231, 0.388] | Complementary partial mediation pattern |

Notes: Indirect estimates are products of standardized regression coefficients (β). Bootstrap CIs are percentile intervals from 3,000 respondent-level resamples. Mediation terminology describes statistical patterns and does not establish causality.
Abbreviations: AIC: Artificial intelligence capability; CI: Confidence interval; FRP: Flood response performance; HRM: Human resource management; LC: Logistics coordination; SE: Standard error.

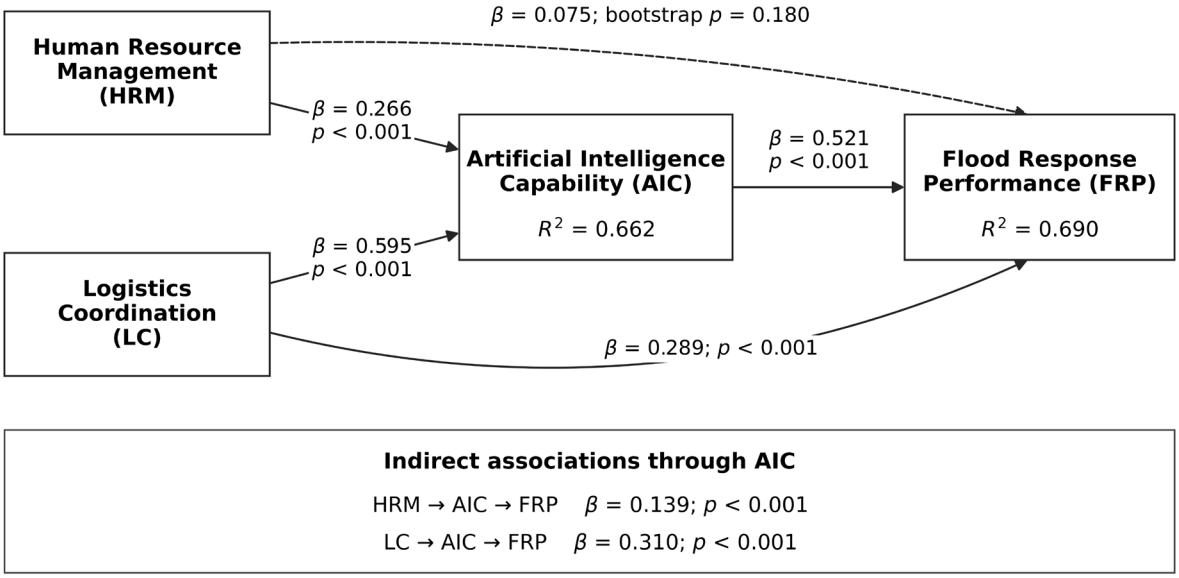



**Figure 3.** Standardized regression associations among HRM, LC, AIC, and FRP. The dashed arrow indicates a nonsignificant association under bootstrap inference; β and $R^2$ represent the standardized OLS coefficient and in-sample explained variance, respectively. Conventional OLS inference yielded $p = 0.037$ for the HRM–FRP association. Arrows indicate hypothesized associations rather than causal effects.
Abbreviations: AIC: Artificial intelligence capability; FRP: Flood response performance; HRM: Human resource management; LC: Logistics coordination; OLS: Ordinary least squares.

effective disaster response. The findings of significant relationships among LC, AIC, and FRP emphasize that digital technologies strengthen institutional governance by improving situational awareness, expediting information sharing, optimizing resource allocation, and facilitating coordinated emergency responses. Therefore, using AI in disaster management helps to strengthen public institutions to deliver more efficient and transparent disaster response services, supporting the broader objectives of SDG 16.

The findings closely align with the national disaster governance framework in Malaysia led by the NADMA.[29] NADMA is the leading agency for disaster coordination, responsible for the implementation of the National Security Council Directive No. 20, which provides the policy and operational mechanisms for disaster management in Malaysia.[30] The directive underscores the importance of professionalizing disaster response personnel, fostering ongoing growth in human capital through simulation

exercises, integrating command systems, and interagency coordination. The significant association of HRM and AIC found in this study supports these policy objectives by indicating that investments in workforce competency, continuous learning, and organizational training are more effective when integrated with AI-enabled decision-support systems. AI does not replace human expertise; rather, it augments the ability of responders to analyze disaster information, prioritize emergency actions, and coordinate complex humanitarian operations across agencies.

Similarly, the substantial effect of LC on both AIC and FRP also corroborates the integrated disaster management philosophy advocated by the National Security Council Directive No. 20.[30] Effective logistics management enables the mobilization of medical teams, medicines, rescue equipment, vehicles, and aid resources in a timely manner across disaster zones. The current findings indicate that AI further strengthens these coordination mechanisms by supporting predictive analytics, intelligent resource allocation, route optimization, and real-time operational monitoring. These abilities are particularly crucial in Malaysia, where flood calamities frequently cross jurisdictional boundaries, necessitating extensive cooperation among governmental bodies, humanitarian entities, and community volunteers.

Additionally, the present research reinforces the strategic objectives delineated in the 12th Malaysia Plan (2021–2025). A key national strategic objective is "Enhancing Security, Wellbeing, and Cohesion," emphasizing disaster risk management, institutional readiness, digital advancement, and organizational robustness.[31] The significant explanatory strength of AIC in this research indicates that forthcoming investments ought to transition from conventional disaster infrastructure to intelligent disaster management systems, predictive analytics, integrated emergency communication platforms, and AI-enhanced decision support systems. These investments align with Malaysia's goals to enhance the provision of public sector services and to bolster national resilience against increasingly frequent climate-related calamities.

The results further validate the priorities established in the Sendai Framework for Disaster Risk Reduction 2015–2030 from a global standpoint. The framework emphasizes the necessity of enhancing disaster risk governance, advancing disaster preparedness, and allocating resources towards resilience-building initiatives via technological advancements.[32] The notable mediating function of AIC highlighted in this research indicates that technology serves as a strategic facilitator in converting organizational resources into enhanced disaster responses. This finding supports international recommendations to embed AI, GIS, remote sensing, big data analytics, and intelligent decision-support systems into national disaster risk reduction strategies.

The findings also have considerable implications for Malaysia's legislative framework, in particular the National Security Council Act 2016 (Act 776), which provides the legal basis for coordinating national security and emergency management during crises.[33] While existing disaster management operations are coordinated using the operational mechanisms laid out by National Security Council Directive No. 20, escalating climate uncertainty and rapid technological advancements necessitate the continuous modernization of disaster governance. The present findings suggest that future disaster management policies should incorporate specific provisions on AI governance, cybersecurity, digital interoperability, standardized data-sharing protocols, and integrated emergency information systems. Such policy improvements enable smooth coordination among NADMA, APM, Fire and Rescue Department Malaysia, Royal Malaysia Police, Department of Irrigation and Drainage, local authorities, and humanitarian agencies.

Overall, this study extends and complements the previous study, showing that effective flood response not only depends on competent human resources and efficient LC, but also on strategic integration of AIC in a robust institutional governance framework.[27] AI serves as a key organizational capability that enables disaster response agencies to optimize their human and logistical resources, fostering organizational resilience and increasing operational effectiveness. This study provides empirical evidence that AIC enhancement, in conjunction with human capital development and integrated LC, can substantially improve Malaysia's flood disaster management system, supporting the objectives of SDG 16,[28] the 12th Malaysia Plan,[31] the National Security Council Directive No. 20,[30] the National Security Council Act 2016,[33] and the Sendai Framework for Disaster Risk Reduction.[32] The findings provide useful guidance to policymakers and disaster management practitioners for developing more resilient, technology-enabled, and institutionally sound disaster response systems capable of addressing future climate-induced flood challenges.

Several limitations constrain interpretation. The cross-sectional design does not establish temporal ordering or causal relationships. Purposive sampling limits population-level generalizability, while questionnaire-based measurement introduces potential common-method influences. F1.11 was removed after examining the earlier results, making this a post hoc measurement

revision requiring independent confirmation. Item–mean correlations and their CR-style and AVE-style summaries do not substitute for a fitted measurement model. HTMT results also indicated sensitivity to the chosen threshold. The direct HRM–FRP association differed in statistical significance between bootstrap and conventional OLS inference. Both results are reported because this sensitivity limits a definitive mediation classification. The analyses used a single dataset and were not validated using independent organizations, another survey period, or operational performance records.

## 5. Conclusion

This study examined the relationships between HRM, LC, AIC, and FRP in Malaysian government agencies and humanitarian organizations in flood disaster management. The regression-based path analysis of observed composite scores showed that both HRM and LC were positively associated with AIC. Conversely, AIC has a significant positive effect on FRP, demonstrating its importance as an organizational capability in disaster management. However, the direct effect of HRM on FRP was not statistically significant; instead, HRM significantly influenced FRP through AIC, indicating full mediation. In contrast, LC had direct and indirect effects on FRP, which confirms partial mediation. The results indicate that the productivity of organizational resources is significantly improved when augmented with AI-enabled capabilities.

This research contributes to the literature of disaster management, extending the earlier research on organizational capabilities by proposing AIC as a mediating construct. Previous studies have mainly focused on the key role of organizational resources and LC in improving disaster response. This research illustrates that digital capabilities serve as the mechanism through which organizational resources translate into improved operational performance. Thus, the findings extend the utilization of the RBV, arguing that technological capabilities have become strategic organizational assets in contemporary humanitarian operations.

Practically, the results provide useful guidance for policymakers, disaster management agencies, and humanitarian organizations. The results support continued investment in workforce competency development, integrated logistics systems, and AI technologies to improve disaster preparedness and emergency response. Organizations should invest in AI-enabled decision-support systems, predictive analytics, intelligent resource allocation, and real-time information sharing to align resources and enhance the coordination of responding agencies. These initiatives will improve operational efficiency, reduce response time, and enhance the overall effectiveness of flood disaster management.

The findings also have important policy implications for Malaysia's disaster governance framework. They align with the strategic objectives of NADMA, National Security Council Directive No. 20, National Security Council Act 2016 (Act 776), and the 12th Malaysia Plan (2021–2025), which emphasizes institutional preparedness, disaster risk governance, digital transformation, and intergovernmental cooperation. Additionally, the investigation contributes to the realization of SDG 16 by enhancing institutional effectiveness, improving public sector governance, and fostering accountable, responsive disaster management systems. These findings are also consistent with the Sendai Framework for Disaster Risk Reduction 2015–2030, which advocates for the implementation of cutting-edge technologies to improve disaster preparedness and resilience.

The revised composite-score analysis identified positive associations between HRM and AIC, LC and AIC, AIC and FRP, and LC and FRP. Significant indirect associations through AIC were observed for HRM and LC. Interpretation of the direct HRM–FRP association was sensitive to the inference method, preventing an unqualified claim of full mediation. Following F1.11 removal, the FRP measurement diagnostics improved. However, conclusions are constrained by construct overlap, the use of observed mean scores, post hoc item removal, and the lack of independent validation. The findings provide preliminary evidence for considering perceived AI capability alongside human-resource and logistics capabilities in flood-response organizations. They do not establish that AI adoption leads to better performance or justify specific technological interventions.

Future research should examine indicator quality, evaluate measurement separation, and replicate the findings in independently collected samples. Subgroup comparisons may be useful where adequately sized groups and comparable measurements are available. Longitudinal designs and recorded outcomes, such as response times and relief-delivery performance, would strengthen assessment of temporal relationships and practical relevance. As a methodological parallel from an external field, a prior study employed cross-site evaluation in solar irradiance forecasting and reported significant variation across locations.[34] Rather than validating the present survey, these findings illustrate why performance in one setting should not be assumed to transfer to another.

Finally, the results show that flood disaster management extends beyond having competent personnel and ensuring efficient logistical coordination. Aligning organizational

resources and AIC strategically may result in sustainable improvements in disaster response, thereby enabling governments and humanitarian organizations to make faster, more informed, and coordinated decisions in emergencies. This study provides empirical evidence from Malaysia for a comprehensive framework to develop institutional resilience and operational effectiveness, with implications for national disaster management priorities and global sustainable development goals.

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## Conflict of interest

The authors declare that they have no conflicting interests.

## Author contributions

*Conceptualization:* All authors
*Formal analysis:* Shaliza Alwi
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*Writing–original draft:* Shaliza Alwi
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## Ethics approval and consent to participate

Research protocols were implemented in accordance with the ethics statement of the Universiti Poly-Tech Malaysia Research Ethics Committee. This work does not contain any proprietary or classified information. All information was gathered in Malaysia in compliance with regional rules and institutional protocols, as declared by the authors. The confidentiality of participants and operational tactics has been protected by the redaction of all organizational names. This study was developed in accordance with Malaysia's National Security Council Directive No. 20 and the national requirements for research related to humanitarian policy and operations. Informed consent was obtained verbally from the participants.

## Consent for publication

Not applicable. This article contains no identifiable participant information.

## Availability of data

This study's findings are supported by data that are available from the corresponding author upon a reasonable request. Availability of these data is subject to certain limitations as a result of confidentiality agreements with the participating organizations.

## AI tools statement

The authors used Grammarly's AI-assisted features to check grammar and improve the clarity and readability. The authors reviewed and approved the suggested edits and take responsibility for the final text.

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