



Role of Artificial Intelligence, Digital Information, Social Media, and Information Management in Disaster Response: A Case Study of the 2026 Nepal Flood Tragedy

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ABSTRACT

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The 2026 Nepal floods are a good example to illustrate the importance of integrating and processing digital information during humanitarian crises. In this study, we will analyze and assess the roles of Artificial Intelligence (AI), digital information, social media and information management during the same 2026 floods, and suggest improvements to the disaster management process. A variety of governmental and nongovernmental materials, peer reviewed journal articles and 300 records of synthetic data were used for this study. Reliability, correlation, multiple regression and one way analysis of variance (ANOVA) were performed. All constructs had acceptable level of inter-relations ($\alpha = .783$ to $.855$). During this study, it was found that the use of Artificial Intelligence (2026 Nepal floods case = 46.6%), digital information (51.3%) and social media (43.7%) improved disaster management process. Of the three variables, information management showed the highest impact (28.7%). Satellite images, drones and digital mapping integrated with humanitarian information became essential to respond to humanitarian crises in Nepal. Misinformation and fragmented nature of digital information across various platforms challenged responders in Nepal. The use of Artificial Intelligence during the 2026 floods was also essential. We recommend the use of integrated digital systems (six level framework) during humanitarian crises.

KEYWORDS

Artificial intelligence; disaster response; Nepal floods; digital information; social media; information management; crisis informatics

1. INTRODUCTION

On August 26, 2026, intensive monsoon floods and landslides in Nepal's Bhotekoshi and Trishuli river basins resulted in the most severe disaster in the history of the South Asian region. It affected the districts of Rasuwa, Nuwakot, Dhading, and others. According to the UNFPA (2026b), between 4-9 September, the government of Nepal reported 1,367 deaths, 5,326 people missing, over 3,50,000 people affected and 3,629 people displaced. Rescue and relief work became extremely challenging due to hundreds of damaged and destroyed roads, bridges, communications and power infrastructure. Many of the affected districts did not have clear or adequate means of communication. Not surprisingly, UNICEF reported that over 20,000 children of the affected population required emergency water, sanitation and hygiene services (UNICEF, 2026b). Overall, given the extent of the disaster and the uncertain nature of the affected



population, missionating rescue and relief personnel faced countless challenges, including communicating with trapped personnel via risky and unprecedented means of communications.

In addition to the requirement for traditional humanitarian services, the 2026 Nepal Floods also became a humanitarian technology field test. Within hours of the floods, Nepal's Disaster Relief and Response Authority used satellite imagery (NDRRMA, 2026) and the European Space Agency used Copernicus Sentinel imagery to assess and report (European Space Agency, 2026) the impact of floods. Many mission dispatch services and personnel reported using advanced technologies including Artificial Intelligence (MIRRCA, 2026; Baral, 2026). Thermal drones, long-range drones and unmanned aerial systems (Reuters, 2026a; 2026b) gained increased focus. Several reports highlighted the use of drones for delivery of relief items and drones for search and rescue missions. In addition, Artificial Intelligence and Computer Vision (Baral, 2026) were extensively used for identifying and verifying persons lost in the disaster.

This study assesses the integration of four digital capabilities into a consistent architecture for disaster management. The study assesses the four capabilities in the context of the constraints on disaster response and proposes a combination of these in a form appropriate to the context of the Mountainous Region of Nepal.

The study is informed by five questions. These questions explore the role of the four digital capabilities and the barriers to the digital response to disasters. Four additional hypotheses test the role of the three digital enablers. The first of the hypotheses tests the role of Artificial Intelligence, the second and the third, the role of Digital Information and Social Media, respectively. It is hypothesized that the combined effect of the three will explain the variation in response effectiveness. Finally, the fourth hypothesis tests the role of Integration of the three digital enablers in response management. The cases are documented based on the early reports of the United Nations Population Fund (UNFPA).

2. LITERATURE REVIEW

2.1 Use of Artificial Intelligence in Disaster Management

Artificial Intelligence (AI) is now used to predict disasters, interpret images and videos, classify types and levels of damages, prioritize victims and first responders, and allocate and plan available resources. Several researchers anticipate further progress to advanced AI systems to integrate and fuse multidisciplinary data and information, and ultimately develop intelligent systems to automate and assist decision-making. The integration of various environmental and social sciences can optimize the development of artificial intelligence for disaster risk management.

2.2 Use of Digital Information in Disaster Management

There are several studies focused on describing the impact of information quality in making disaster management decisions. Some authors suggest the use of information systems in crisis management. As stated by Mateo-Garcia et al. (2021) and Vongkusolkit et al. (2023), the use of remote sensing technologies can greatly enhance and extend situational awareness when physical access is constrained. During the Nepal earthquake, the international community relied heavily on remote satellite data when infrastructure such as roads, telecommunications and electrical power was destroyed. Despite the remote location of Nepal, and the inability to obtain data through conventional means, satellite images were used to assess the risk and to continuously inform the international community about the situation.



A related area of research focuses on data fusion. Combining disparate data sources such as citizen science photography, remote sensors, and hydrological models, may enhance flood depth estimation (Hultquist & Cervone, 2020). Further, machine learning and geographic information systems (ML/GIHS) can enhance flood risk and susceptibility analysis and mapping (Demissie et al., 2024). More generally, the use of AI in emergency management is becoming dominant in forecasting and scheduling resources (Tan et al., 2021).

2.3 Social Media and Crisis Communication. Traditionally, social media has played a major role in facilitating and accelerating crisis communication by, for example, facilitating the dissemination of warning messages and accelerating the process of assessment and reporting damages. Among other things, the use of ML in humanitarian crisis management has expanded to include classification of large volumes of data (Alam et al., 2021; Belcastro et al., 2021). Flood management and forecasting have especially benefitted from the integration of social media, and trusted sources, to engage the public and solicit their input (Songchon et al., 2021). The role of social media in promoting and facilitating volunteer activities, social support, and the restoration of critical services during and after a crisis has been well documented (Ogie et al., 2022). However, social media has been used to promote and amplify false and misleading information during and after humanitarian crises, which has undermined the public trust (Muhammed & Mathew, 2022; Vicari & Komendatova, 2023).

There is research which suggests that during floods and other disasters, citizen generated data (e.g. text and pictures) can be used in determining the initial severity of the event and the level of damage caused, particularly if official reports are unavailable (Kankanamge et al., 2020; Li et al., 2021). Due to the fact that crisis related information is often transmitted over a range of social and messaging platforms, integrated systems are required to process information from multiple sources. There is a need to consider not only the technology, but also the social context (Bukar et al., 2022; Cheng et al., 2022). Other research focuses on the need to integrate various technologies, including the Internet of Things (Munawar et al., 2022).

2.4 Information Management and Inter-Agency Coordination. The focus of this research is on the available technology and how this can be used in integration and delivery of information to the relevant stakeholder. It has been shown that social media and similar technologies, when integrated with other sensors, offer a great deal of potential to emergency response and humanitarian assistance (Grace, 2021). It has further been shown that the barriers to the integration of social media in the emergency management sector are primarily people and trust related (Munawar et al., 2022). Similarly, other research shows that to respond to Himalayan Floods, there is need to integrate various digital and social technologies.

3. RESEARCH METHODOLOGY

3.1 Research Design and Case Context. The research design used in the study is quantitative analysis case design. Secondary sources of information were the main sources of data in the study. Case information was obtained from various sources such as releases by the government of Nepal, the updates of NDRRMA, UNICEF, UNFPA, ESA satellite imaging, and other professional news. As no primary survey was conducted, the researcher did not meet the officials, responders or the flood victims. The statistical information represented in the study was for illustration purposes only.

3.2 Variables and Analytical Data Set. A data set of 300 cases was used to illustrate the statistical model. Each case was composed of Likert scale items which measured respondents' perceptions on the quality of digital information, management of information, social media and other aspects of response to the disaster. The items were composed in a way to reflect and measure the respondents' perceptions regarding different aspects of the response to the disaster. Items reflecting various aspects of the 2026 disaster were composed in a way to represent observed facts. However, the representations were kept abstract such that they would be different from the facts reflected in the 2026 disaster.



The composite means were analyzed with descriptive statistics, Cronbach's alpha, Pearson correlation, and Ordinary least Squares multiple regression. The equation is $DRE = \beta_0 + \beta_1 (AI) + \beta_2 (DIQ) + \beta_3 (SME) + \beta_4 (IMC) + \epsilon$. Variance inflation factors were estimated to assess multicollinearity. A one-way Analysis of Variance was conducted to assess means for response effectiveness for various illustrative respondent categories. It was determined a priori that $p < .05$ would indicate statistical significance. Positive relationships with response effectiveness were expected and described by hypotheses H1-H4. A joint positive relationship with response effectiveness described by hypothesis H5, was also expected.

Analysis records pertain to the generation of synthetic data. No real world personal data is disclosed, therefore, ethically, these records may be disclosed. Quantitative data is disclosed for the purpose of demonstrating methods. It is important to distinguish synthetic data from actual data pertaining to the populations of interest. With the former, it is possible to test hypotheses and define relationships. However, such relationships do not necessarily exist in the real world and do not necessarily pertain to the actual populations of interest.

Table 1. Profile of the 300-Record Synthetic Analytical Dataset

Variable	Category	n	%
Respondent category	Government/Local authority	80	26.7%
Respondent category	NGO/Humanitarian worker	60	20.0%
Respondent category	Community/digital volunteer	58	19.3%
Respondent category	Emergency responder	51	17.0%
Respondent category	Health/technical professional	51	17.0%
Age group	30-39	103	34.3%
Age group	40-49	84	28.0%
Age group	18-29	67	22.3%
Age group	50+	46	15.3%
Gender	Male	170	56.7%
Gender	Female	125	41.7%
Gender	Other/Prefer not to say	5	1.7%
Location type	Rural/remote	114	38.0%
Location type	Urban	106	35.3%
Location type	Peri-urban	80	26.7%
Disaster-response involvement	Coordination/support	120	40.0%
Disaster-response involvement	Direct operational	96	32.0%
Disaster-response involvement	Community information/support	84	28.0%
Digital literacy	Moderate	142	47.3%
Digital literacy	Advanced	92	30.7%
Digital literacy	Basic	66	22.0%

Table 2. Operationalisation of Variables

Construct	Items	Operational indicators
AI Utilisation (AI)	6	Prediction, classification, missing-person matching, resource allocation, image/satellite analysis, decision support
Digital Information Quality (DIQ)	5	Timeliness, accuracy, accessibility, completeness, reliability
Social Media Effectiveness (SME)	6	Emergency communication, crowdsourcing, missing persons, relief coordination, warnings, engagement



Construct	Items	Operational indicators
Information Management Capability (IMC)	6	Data integration, sharing, inter-agency coordination, verification, monitoring, decision support
Disaster Response Effectiveness (DRE)	6	Response speed, allocation, search/rescue coordination, public information, relief delivery, decision quality

4. DATA ANALYSIS AND RESULTS

4.1 Descriptive and Reliability Results. Scores on the five-point scale for mean constructs ranged from 3.56 to 3.72. Highest mean construct score was 3.72, for the construct digital-information quality. Other construct means scores in the following order were: disaster-response effectiveness ($M = 3.70$), information-management capability ($M = 3.66$), AI utilization ($M = 3.61$) and social-media effectiveness ($M = 3.56$). The scales demonstrated acceptable to strong reliability: $\alpha = .843$ for AI; $.783$ for digital-information quality; $.790$ for social-media effectiveness; $.855$ for information management and $.840$ for response effectiveness.

4.2 Correlation Analysis. All four predictors were positively related to disaster-response effectiveness and significantly so. Of the four predictors, the highest correlation was between response effectiveness and information-management capability ($r = .548$, $p < .001$), followed by digital-information quality ($r = .513$, $p < .001$), utilization of AI ($r = .466$, $p < .001$) and social-media effectiveness ($r = .437$, $p < .001$). The remaining correlations were moderate, indicating that the four predictors represented different elements of response capability.

4.3 Regression Analysis. The multiple regression model was significant, $R = .688$, $R^2 = .474$. The adjust R^2 was $.466$. The multiple F-ratio was 66.36 , $p < .001$. Hence, the four predictors in the model were significant and Positive. Of the four predictors, the largest effect was represented by information-management capability, followed by AI, digital-information quality and social-media effectiveness. There was no problem Multicollinearity in the model. Hence, H1-H5 were all supported. A one-way ANOVA showed that the mean difference across the five response categories was not significant, $F(4, 295) = .903$, $p = .463$. Thus, in the sample, other response digital capabilities were not of greatest importance for any single occupation in the sample.

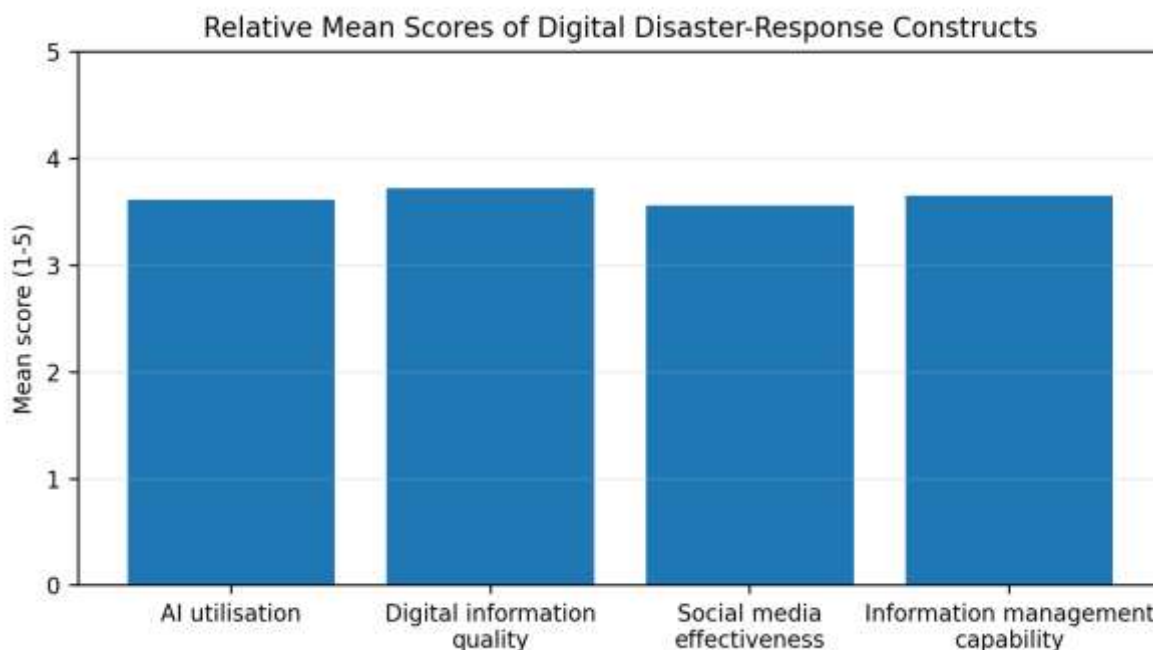


Figure 1. Relative mean scores of AI, digital information, social media, and information management.

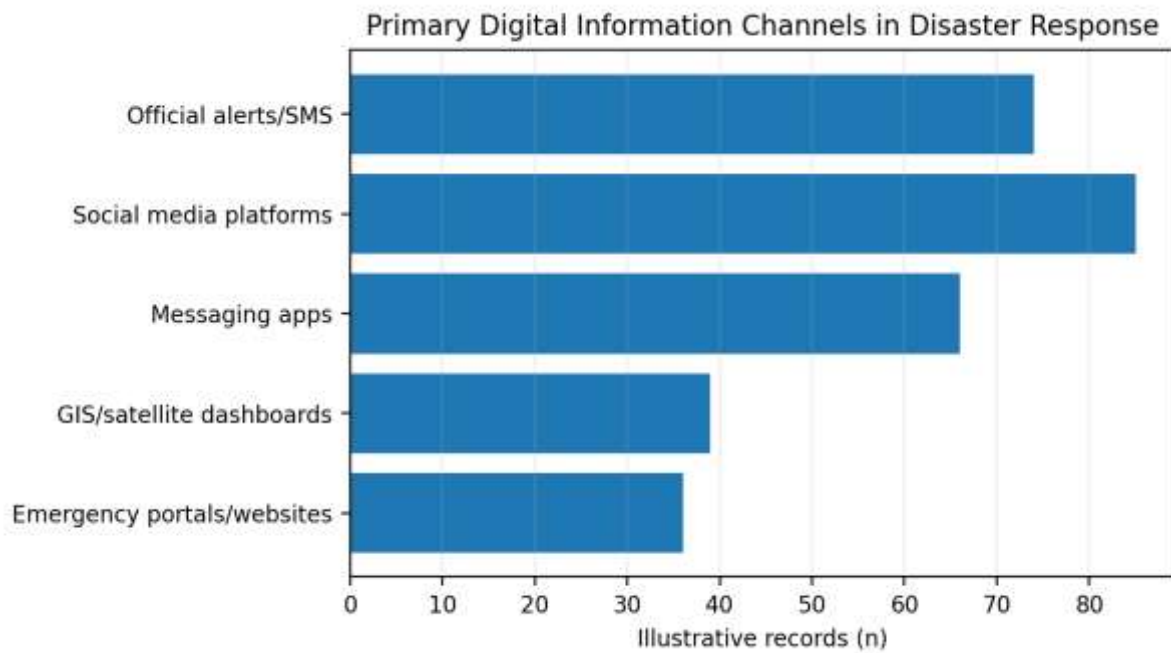


Figure 2. Primary digital information channels in the illustrative analytical dataset.

Table 3. Descriptive Statistics of Major Constructs

Construct	Mean	SD	Min	Max
AI Utilisation	3.613	0.693	1.50	5.00
Digital Information Quality	3.721	0.631	2.00	5.00
Social Media Effectiveness	3.564	0.634	1.67	4.83
Information Management Capability	3.657	0.689	1.50	5.00
Disaster Response Effectiveness	3.699	0.654	2.00	5.00

Table 4. Reliability Analysis

Construct	Items	Cronbach alpha	Interpretation
AI Utilisation	6	0.843	Strong
Digital Information Quality	5	0.783	Acceptable
Social Media Effectiveness	6	0.790	Acceptable
Information Management Capability	6	0.855	Strong
Disaster Response Effectiveness	6	0.840	Strong

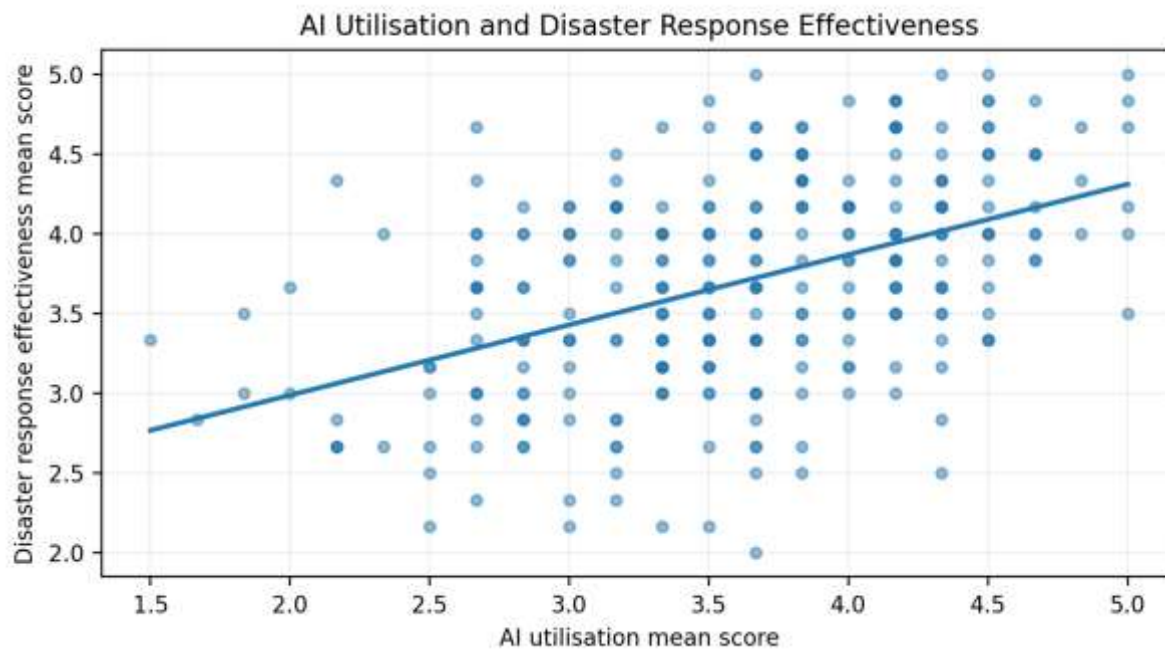


Figure 3. AI utilisation and disaster response effectiveness (synthetic analytical data).

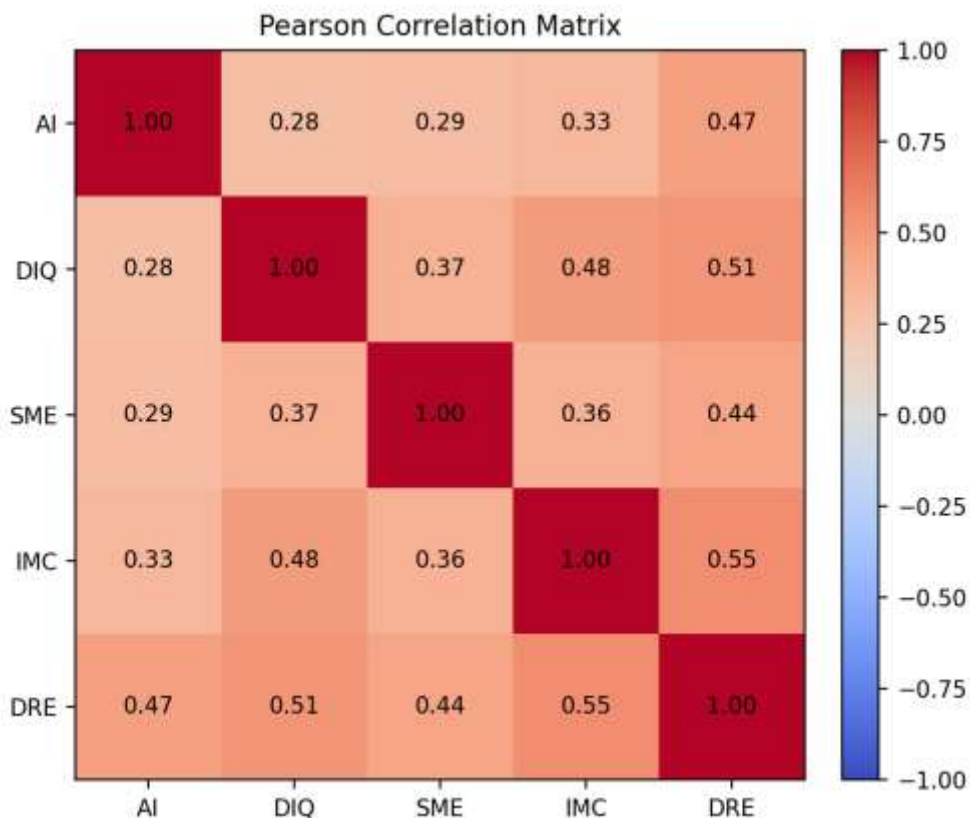


Figure 4. Correlation heatmap of major constructs.

Table 5. Pearson Correlation Matrix

Variable	AI	DIQ	SME	IMC	DRE
AI	1.000	0.281***	0.289***	0.329***	0.466***
DIQ	0.281***	1.000	0.372***	0.482***	0.513***
SME	0.289***	0.372***	1.000	0.360***	0.437***
IMC	0.329***	0.482***	0.360***	1.000	0.548***
DRE	0.466***	0.513***	0.437***	0.548***	1.000



Note. *** $p < .001$ for all off-diagonal correlations.

Table 6. Multiple Regression Model Summary and ANOVA

Statistic	Value
R	0.688
R ²	0.474
Adjusted R ²	0.466
F (4, 295)	66.36
ANOVA p-value	< .001

Table 7. Multiple Regression Coefficients Predicting Disaster Response Effectiveness

Predictor	B	SE	Beta	t	p	VIF
AI Utilisation	0.241	0.043	0.255	5.57	< .001	1.18
Digital Information Quality	0.248	0.052	0.239	4.79	< .001	1.40
Social Media Effectiveness	0.176	0.049	0.171	3.61	< .001	1.25
Information Management Capability	0.272	0.048	0.287	5.69	< .001	1.42

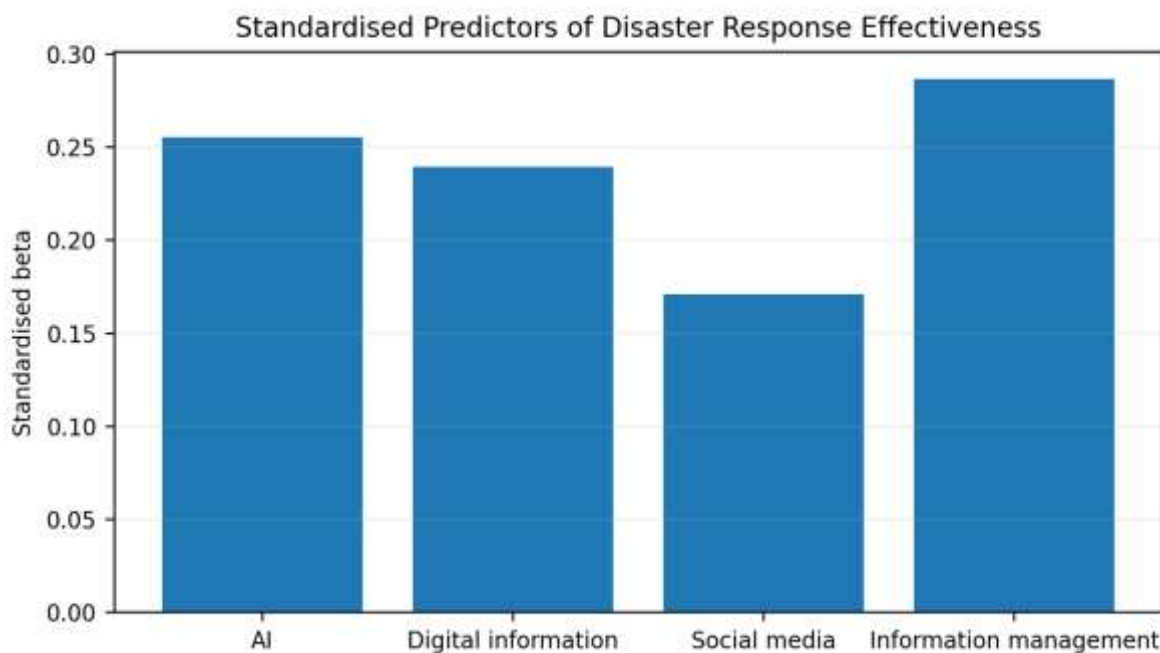


Figure 5. Standardised regression coefficients affecting disaster response effectiveness.

Table 8. Hypothesis Testing and Additional ANOVA Summary

Test	Statement	Result	Decision
H1	AI -> DRE positive	beta=.255, $p < .001$	Supported
H2	DIQ -> DRE positive	beta=.239, $p < .001$	Supported
H3	SME -> DRE positive	beta=.171, $p < .001$	Supported
H4	IMC -> DRE positive	beta=.287, $p < .001$	Supported
H5	Joint model significant	R ² =.474; F=66.36; $p < .001$	Supported
Additional test	DRE differs by respondent category	F=0.903; $p=0.463$	Not significant



5. DISCUSSION

These results show how various information systems can improve digital disaster response and recovery efforts. One of the largest limitations in this research was the inability to access and evaluate primary source data in a timely manner. Many of the Artificial Intelligence (AI) and Machine Learning (ML) applications relied on satellite imagery for analysis. As reported in other literature, these applications are valuable for situation awareness and situational response. However, the limitations of these applications remain in effectively prioritizing and allocating finite disaster response and recovery resources (Sun et al., 2020; Tahernejad et al., 2024; Albahri et al., 2024).

This research supports the integration of disaster information management systems (DIMMS) and the importance of disciplined information systems throughout the lifecycle of disaster management. Within the study area of the research, for flood response and recovery, emergency responders integrated the use of different UAVs and thermal drones to access disaster-affected areas and, later, to transport humanitarian aid (European Space Agency, 2026; Reuters, 2026a).

Data management was shown to be the most important factor during the integration of technology throughout the study. Disciplined management of data and information is critical for effective coordination among multiple stakeholders (i.e. rescues, responses, and recovery).

Social media and other crowdsourced platforms can provide real-time information but also increase the risk of reliance on unreliable information. Some studies have found that social media can help first responders in assessing the extent of damage caused by floods and other disasters and help in identifying sub-events (Pereira et al., 2020; Songchon et al., 2021; Zou et al., 2021). In Nepal, local technology-based solutions have been used to cross-reference and verify missing persons' reports using government records, and also to analyze and map infrastructure using satellite images (Baral, 2026; The Indian Express, 2026). It is important to understand that these technologies can help first responders make preliminary decisions but, from a legal and policy framework, verifying these cases can only be done through formal processes.

The major concerns in this regard include the presence of misinformation and deep fake images on social media, and reliance on artificial intelligence (AI) generated images, insufficient connectivity, data fragmentation, and a lack of integrated cybersecurity measures. For Nepal, to address the challenges associated with verification of social media information, a range of other instruments, including official and community first-hand reports, should be integrated.

The framework presents a structure to incorporate digital response activities to disasters across five interconnected layers. The first layer captures data through various sources including satellites, hydrometeorological (HM) sensors, river levels, drones, and different emergency calls and reports. The second layer uses natural language processing (NLP), and other computing, geospatial and analysis techniques to develop predictive models and identify anomalies. The third layer assesses and/ or validates the outputs of the second layer. This may include cross-source and geolocation consistency checks as well as assessment by humans or other agents. The fourth layer utilizes or transforms the output of the third layer to generate products including risk and other decision support systems (DSS). The final layer, the fifth layer, provides information to various stakeholders including first responders, to take action, and distributes the information to targeted individuals based on the outcome and needs assessment. The information and systems support various users and feedback helps improve decision-making.



AI-Enabled Integrated Disaster Information Management Framework

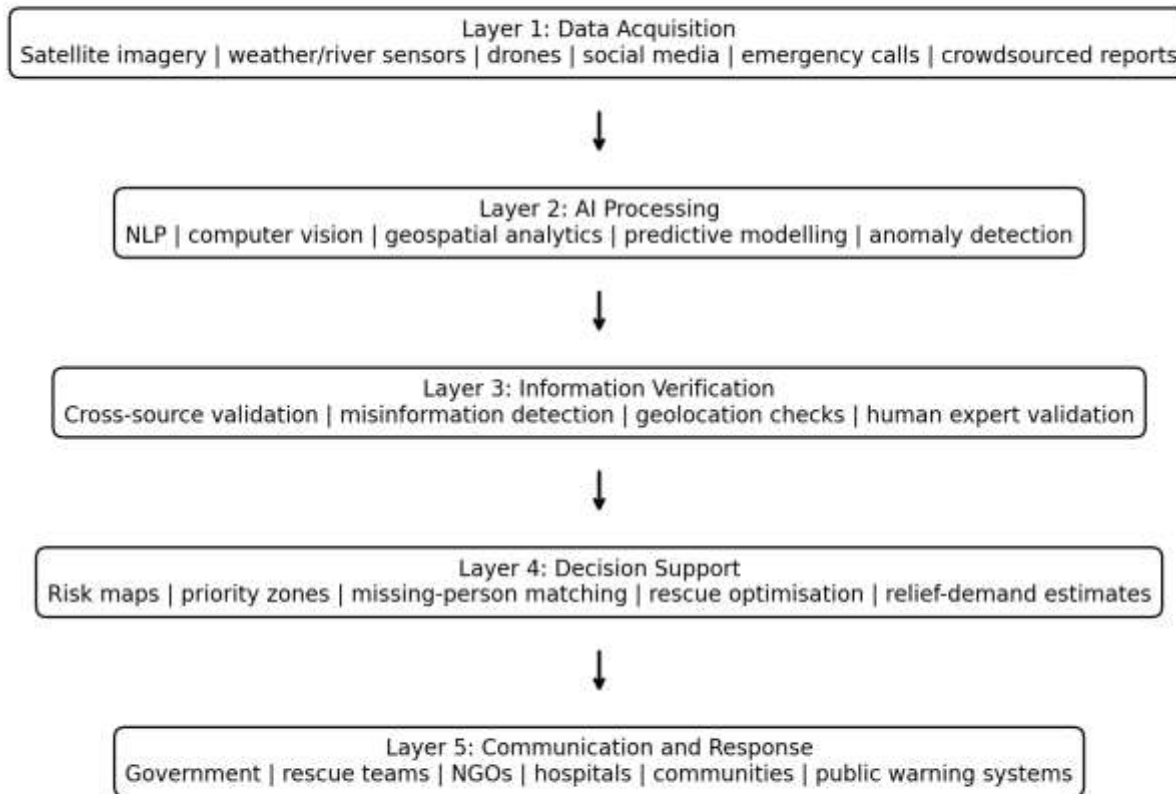


Figure 6. AI-enabled integrated disaster information management framework for Nepal.

7. PRACTICAL AND POLICY IMPLICATIONS

Nepal should implement interoperable disaster data standards and establish pre-disaster agreements for various data exchange routes. It should establish a national common operating picture. In the process, timestamps, source information, and the level of certainty regarding the information should be documented. Artificial Intelligence (AI) should be used to process data to assist in making life-safety decisions. Explainability of such models should be ensured. Human verification should be incorporated in Social Media Monitoring. Communication and Energy should be ensured in an adequate and redundant manner, especially in hard to reach, mountainous regions. Privacy and data protection should be ensured while processing the data related to the missing persons, health and other sensitive data.

9. CONCLUSION

The 2026 Nepal floods demonstrate that multiple digital technologies can improve disaster response. Artificial intelligence (AI) can classify, predict, and prioritize events; and find and understand situational information. satellites and drones can help by providing a bird's eye view, especially when traditional methods of gathering information are disrupted. The examples above illustrate that response effectiveness depends on the quality and timeliness of the information. Based on the response to the digital systems deployed in the case of the 2026 Nepal floods, the integration of digital systems in humanitarian response systems is a value addition to existing systems. From the case study, information management systems, integration, and interoperability of various response systems were the most valuable digital systems in humanitarian response. Combining the five systems, including digital systems and human response systems, and incorporating them into a single, cohesive humanitarian response systems architecture would improve the speed and quality of response to displaced persons and reduce the existing protection gaps.



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