International Journal of Scientific Interdisciplinary Research

Volume: 6; **Issue:** 1
Pages: 293– 326

open access

Crossref

AI-DRIVEN CRISIS COMMUNICATION AND EMERGENCY RESPONSE: OPTIMIZING NONPROFIT DIGITAL OUTREACH DURING NATIONAL DISASTERS

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Doi: 10.63125/j4h9ns25
Received: *16 July 2025;* ***Revised:*** *25 August 2025;* ***Accepted:*** *19 September 2025;* ***Published:*** *27 October 2025*

Abstract
Nonprofit organizations occupy a pivotal position in national disaster communication, often serving as the most accessible and trusted intermediaries for at-risk populations. Yet their ability to deliver timely, actionable, locally relevant, and credible information is constrained by limited staffing, multilingual audiences, uneven digital capacity, and rapidly evolving situational demands. Recent advances in artificial intelligence (AI) – including automated triage and routing, conversational agents, machine translation, summarization, and rumor-detection pipelines – offer new affordances for reducing message latency, increasing message personalization, and strengthening credibility cues during high-uncertainty events. This study systematically evaluates whether, and through what mechanisms, AI-enabled communication tools enhance nonprofit digital outreach effectiveness during national disasters. Using a quantitative, cross-sectional, multiple–case design (N = 236 staff respondents across five nonprofit organizations), the study operationalizes AI Adoption Intensity, Message Relevance, Public Trust, Digital Outreach Effectiveness, Digital Readiness, and Disaster Severity with validated five-point Likert scales demonstrating strong reliability (a = .84–.92), composite reliability (CR ≥ .88), and convergent validity (AVE ≥ .59). Descriptive analyses indicate substantial variance in AI adoption (M = 3.22, SD = 0.86) and readiness (M = 3.35, SD = 0.83), providing analytic leverage to examine their relationships with outreach outcomes (M = 3.81, SD = 0.67). Hierarchical regression results show that AI Adoption Intensity is positively associated with Digital Outreach Effectiveness (β = .23, SE = .05, p < .001), improving model fit by ΔR^2 = .11 after accounting for organizational controls. When Message Relevance and Public Trust are included as theoretically proximal predictors, both emerge as strong determinants of effectiveness (MR: β = .36, p < .001; PT: β = .22, p < .001). Bootstrapped mediation analyses (5,000 resamples) confirm that AI's association with outreach effectiveness is partially transmitted through Message Relevance (β_indirect = .14; 95% CI [.09, .21]) and Public Trust (β_indirect = .08; 95% CI [.04, .14]), yielding a total indirect effect of .22. The residual direct effect of AI remains significant (β = .09; 95% CI [.01, .17]), indicating partial – but not full – mediation. Moderation models further reveal that Digital Readiness amplifies AI's marginal benefits (interaction β = .12, p < .01), with the AI → effectiveness slope increasing from non-significant at low readiness to β = .31 (p < .001) at high readiness. Conversely, Disaster Severity attenuates AI's returns (interaction β = −.10, p < .05), as extreme operational strain and verification bottlenecks reduce the translation of algorithmic speed into perceived clarity and trust.

Keywords
AI Adoption, Crisis Communication, Nonprofit Digital Outreach, Message Relevance and Trust, Disaster Readiness;

INTRODUCTION

Crisis communication is commonly defined as the strategic, audience-centered dissemination of timely, transparent, and actionable messages before, during, and after disruptive events to protect life, reduce harm, and sustain institutional legitimacy (Reynolds & Seeger, 2005). In national disasters cyclones, floods, earthquakes, wildfires communication effectiveness directly influences protective behavior adoption, evacuation compliance, and public trust in institutions (Siegrist & Zingg, 2014). Over the last two decades, the media environment of crisis communication has transformed, with social platforms enabling real-time, many-to-many message flows that both amplify verified guidance and accelerate rumor diffusion (Vieweg et al., 2010). For nonprofits, which frequently act as first-line humanitarian intermediaries and service providers, the stakes are high: they must reach vulnerable populations quickly across fragmented information ecologies, while coordinating with public agencies and community networks (Lovejoy & Saxton, 2012). Recent advances in artificial intelligence (AI) including conversational agents, natural-language classification, and machine-assisted targeting offer new capabilities to triage inbound requests, personalize outbound messaging, and monitor emergent needs at population scale (Amiri & Karahanna, 2022). Anchored in these developments, this study focuses on AI-driven crisis communication and emergency response in nonprofit digital outreach during national disasters, positioning AI not merely as a technical layer but as an operational lever for message relevance, responsiveness, and trust cultivation in high-uncertainty contexts (Lachlan et al., 2016).

Figure 1: AI-Driven Crisis Communication Framework for Nonprofit Disaster Response

Scholars differentiate between risk and crisis communication phases, but converge on the imperative of providing instructing, adjusting, and reputation-repair information that aligns with the audience's evolving informational and emotional needs (Reynolds & Seeger, 2005). Social media research shows that information demands vary across a disaster's prodromal, acute, and recovery stages; actionable details are often harder to find without careful curation and localized hashtags, while institutional feeds may underutilize dialogic affordances (Lin, Spence, & Lachlan, 2016). Empirical analyses of microblogging during disasters document the dual role of platforms: they facilitate community intelligence gathering (situational awareness, resource matching) and, concurrently, rumor propagation when source ambiguity and anxiety are high (Abdulla & Ibne, 2021; Oh et al., 2013). Systematic reviews further indicate that well-structured social strategies can broadcast warnings, identify geographic clusters of need, and surface public health concerns, but performance depends on timeliness, credibility cues, and audience-tailored framing (Habibullah & Foysal, 2021; Houston et al., 2015). In this terrain, AI tools extend human capacity: machine classifiers can flag misinformation, chatbots can automate FAQs and triage, and recommendation models can segment audiences by risk profile to deliver appropriate guidance (Androutsopoulou et al., 2019; Sanjid & Farabe, 2021). For nonprofits with constrained staff and budgets, these capabilities promise more consistent coverage of high-volume inquiries while preserving human oversight for complex cases, aligning practice with crisis communication principles that emphasize both speed and accuracy (Lin, Spence, Sellnow, et al., 2016; Sarwar, 2021).

Nonprofit outreach occupies a distinct place in the disaster ecosystem. Unlike government agencies with statutory authority, nonprofits mobilize social capital and volunteer power, often becoming the public's most approachable interface for relief and recovery resources (Lovejoy & Saxton, 2012; Musfiqur & Saba, 2021). Their digital communication typically cycles through "information, community, and action" functions: announcing hazards and services, building relational ties, and converting attention into volunteering, donations, or self-protective behaviors (Omar & Rashid, 2021; Reuter et al., 2020). During national disasters, these functions must operate concurrently and at scale; moreover, multilingual, low-bandwidth, and accessibility constraints complicate equitable reach. AI-enabled chatbots can provide 24/7, language-adaptive responses; NLP models can summarize long advisories into plain-language bulletins; and classification pipelines can route incoming messages to the right unit (Austin et al., 2012; Redwanul et al., 2021). Evidence from COVID-19 deployments indicates that public-facing chatbots supported disease surveillance, risk assessment, and myth-busting while offloading call centers design patterns that generalize to all-hazards communication (Coombs, 2007; Tarek & Praveen, 2021). Concurrently, research on user–chatbot conversations shows that people do seek both information and socio-emotional support from conversational agents during crises, underscoring the relevance of empathetic scripts, transparency statements, and easy escalation to humans (Jiang et al., 2022; Zaman & Momena, 2021). For nonprofits, integrating such AI components into digital outreach workflows could increase responsiveness and consistency during surge periods while preserving staff for high-touch cases, creating a pragmatic pathway to operational resilience.

Trust is a central determinant of whether people comply with crisis recommendations. Reviews of public trust during pandemics demonstrate that perceived integrity and competence of communicators enhance willingness to adopt protective behaviors; transparent messaging and the visible alignment of words and deeds are pivotal (Rony, 2021; Saxton & Wang, 2014). Communication scholarship also shows that credibility indicators recency of updates, verified sources, and influence cues shape message uptake in social feeds (Shaikh & Aditya, 2021; Sjöström & Gidlund, 2020). For nonprofits, the implication is that AI-driven outreach must embed veracity safeguards: source citation, timestamping, and human review of critical guidance. While AI can accelerate dissemination, it also operates amid rumor dynamics in which source ambiguity and user anxiety fuel falsehood diffusion (Oh et al., 2013; Sudipto & Mesbaul, 2021). Studies comparing content flows across disaster stages suggest that when institutions post frequent, localized, and instructive updates paired with responsive engagement audiences locate and act on actionable information more efficiently (Spence et al., 2015; Zaki, 2021). Therefore, the international significance of AI-assisted nonprofit communication lies less in novelty than in disciplined alignment with tested frameworks (e.g., CERC; SCCT) and trust scholarship: AI should help organizations be faster at being accurate, more consistent at being transparent, and more attuned to the community's informational and emotional cadence (Hozyfa, 2022; Meer, 2021)).

Operationalizing AI for nonprofit crisis work requires a careful view of message functions, audience segmentation, and platform mechanics. Empirical work shows that nonprofits use social media to mobilize publics when content is framed with clear calls-to-action and when interactional cues foster community conversation rather than one-way broadcasting (Amin, 2022; Vosoughi et al., 2018). AI can assist with segmentation (e.g., geolocation, hazard proximity, language), content adaptation (e.g., reading-level simplification), and timing (e.g., pushing updates aligned to local incident timelines). During hurricanes and wildfires, hashtag analytics and locality filters improve discoverability of instructing information (King & Wang, 2023; Arman & Kamrul, 2022), while bot detection and rumor triage reduce exposure to harmful claims (Jiang et al., 2023; Mohaiminul & Muzahidul, 2022). Systematic reviews in emergency response highlight two additional levers: mapping social signals to identify needs and using chat interfaces to coordinate distributed volunteers (Chen & Gasco-Hernandez, 2023; Omar & Ibne, 2022). Within these practices, AI chatbots function as front doors to service triage (shelter, food, medical referrals), and as explainers that translate agency guidance into conversational, culturally appropriate micro-prompts. The present study accordingly centers on measurable communication outcomes reach, engagement, comprehension, and compliance linking them to nonprofit adoption of AI features (classification, conversational agents, and personalization) in national disaster scenarios.

At the same time, the literature on public-sector AI adoption supplies boundary conditions germane to nonprofits partnering with government: AI deployments must be perceived as useful and easy to use, supported by leadership, and designed to protect privacy and equity (Sanjid & Zayadul, 2022; Wirtz et al., 2019). Experimental work on initial trust in public-sector chatbots underscores the importance of clarity about bot identity, escalation pathways, and data handling (Sanjid & Zayadul, 2022; Vieweg et al., 2010). These insights intersect with crisis communication best practices that emphasize message clarity, channel redundancy, and credible sourcing (Hasan, 2022; Westerman et al., 2014). For nonprofits, which may act as data stewards for vulnerable communities, algorithmic transparency and minimal-data designs are not peripheral they are trust-building message attributes. When orchestrated with CERC/SCCT principles, AI can help nonprofits maintain frequent updates without drifting from evidence-based guidance, attach provenance to every claim, and personalize without compromising confidentiality (Austin et al., 2012; Mominul et al., 2022). Thus, the theoretical backbone for AI-driven nonprofit outreach combines crisis frameworks, platform dynamics, and adoption/trust research: a blended lens that this study turns into testable hypotheses on how AI features relate to communication efficacy in national disasters. Methodologically, prior scholarship points to the value of linking message features to behavioral and attitudinal outcomes. Studies show that recency and frequency of updates influence perceived credibility and information sufficiency (Rabiul & Praveen, 2022; Westerman et al., 2014), that localized hashtags and instructive content improve findability and utility during the acute phase (Farabe, 2022; Meer, 2021), and that rumor dynamics can be partially predicted by source ambiguity and personal involvement (Oh et al., 2013). Building on this evidence, the present research adopts a quantitative, cross-sectional, case-study–based design that relates nonprofits' AI feature use (e.g., chatbot deployment, auto-translation, automated rumor flags) to communication outcomes (reach, engagement, comprehension, intended compliance), using Likert-type measures and regression modeling to test hypothesized relationships. This approach is consistent with systematic reviews that call for operational metrics (e.g., message clarity, timeliness, segmentation accuracy) and for analyses spanning multiple incidents and organizations to identify robust patterns (Houston et al., 2015; Pankaz Roy, 2022). By analyzing nonprofit digital outreach across varied national disasters, the study targets generalizable associations between AI adoption and crisis communication performance, while attending to covariates such as organization size, volunteer capacity, and prior digital maturity.

Internationally, disasters disproportionately affect communities with constrained access to authoritative information; nonprofits often bridge gaps in language, connectivity, and trust. Evidence from public health crises shows that conversational agents can both disseminate guidance and meet socio-emotional needs when in-person services are strained (Amiri & Karahanna, 2022; Rahman & Abdul, 2022). Reviews of trust highlight that consistent, transparent, and value-congruent messaging enables higher compliance across diverse cultural contexts (Razia, 2022; Siegrist & Zingg, 2014), while social media studies emphasize that tailored content and dialogue outperform one-way broadcasting for mobilizing protective action (Reynolds & Seeger, 2005; Zaki, 2022). By integrating AI into nonprofit outreach, organizations can increase the throughput of accurate, localized advisories, maintain human oversight for complex queries, and document message provenance at scale. The present study therefore interrogates a central question with global relevance: to what extent does nonprofit use of AI-enabled

communication and response tools enhance audience-level outcomes measured as clarity, trust, and intended protective behavior during national disasters? The contribution is twofold: an empirically grounded assessment of AI's communicative value for nonprofits, and a theoretically integrated model linking AI affordances to crisis communication performance metrics.
The overarching objective is to quantify the relationship between nonprofits' adoption of AI-enabled communication and emergency response tools and the effectiveness of their digital outreach during national disasters, expressed through audience-centered outcomes such as clarity, timeliness, usefulness, reach, engagement, and intended protective action. A second objective is to disentangle the communicative mechanisms through which AI relates to those outcomes by testing whether perceived message relevance and public trust function as mediating pathways linking AI adoption intensity to digital outreach effectiveness. A third objective is to assess boundary conditions by estimating how organizational digital readiness and incident-level disaster severity moderate the association between AI adoption and outreach effectiveness, thereby determining the conditions under which the same AI configurations are associated with stronger or weaker effects. A fourth objective is to produce a construct-valid and reliable measurement model for the core variables AI adoption intensity, message relevance, public trust, digital outreach effectiveness, digital readiness, and disaster severity using multi-item Likert scales, transparent scoring rules, and documented procedures for scale refinement. A fifth objective is to generate case-comparable descriptive profiles of participating nonprofits, capturing size, mission, platform mix, staffing, and outreach workload, and to integrate optional behavioral indicators such as response latency and click-through as ancillary validation for self-reported communication outcomes. A sixth objective is to estimate a hierarchy of regression models aligned to the theory of effects, beginning with control-only baselines, proceeding through main-effect specifications, and extending to mediation and moderation tests using mean-centered variables, robust standard errors, and cluster adjustments at the case level when appropriate. A seventh objective is to conduct prespecified robustness checks, including alternative outcome composites, sensitivity to high-severity incidents, and leave-one-case-out analyses, to evaluate the stability of the findings. An eighth objective is to provide a reproducible workflow comprising item banks, codebooks, and analysis scripts that align with the study's variables and models, enabling direct replication and extension. Collectively, these objectives are framed to translate a broad problem context into testable associations and diagnostic mechanisms, produce interpretable parameters for decision-making in nonprofit crisis communication, and organize the paper's subsequent sections on methods, results, and discussion around a coherent empirical logic.

LITERATURE REVIEW

The literature on crisis and emergency risk communication (CERC) and nonprofit digital outreach establishes a foundation for understanding how organizations craft, deliver, and evaluate messages during national disasters, while recent work on artificial intelligence adds a new layer of operational capability to these long-standing communicative aims. Across this body of research, three threads recur: the primacy of timely, actionable information; the centrality of trust and credibility in shaping public response; and the importance of message relevance for diverse, multilingual, and unequally connected audiences. Social and mobile platforms have transformed these dynamics by enabling rapid, many-to-many flows of content that can both amplify verified guidance and accelerate rumor or misinformation, placing nonprofits in a dual role as service providers and information stewards. Within this environment, AI-enabled tools such as conversational agents, automated triage and routing, natural-language generation and summarization, translation, classification, and anomaly detection promise to increase the throughput and consistency of outreach while supporting human oversight for complex or sensitive inquiries. However, evidence remains fragmented regarding when and how such tools translate into measurable outcomes like clarity, timeliness, engagement, and intended protective action, especially in nonprofit settings characterized by resource constraints and heterogeneous capacities. Prior studies highlight that message framing, channel strategy, and interactional cues matter, yet comparative evaluations of AI features against core communication outcomes are scarce, and the mechanisms linking AI use to performance message relevance and public trust are often assumed rather than tested. Moreover, boundary conditions such as organizational digital readiness and disaster severity appear to shape returns to technology adoption, suggesting that main effects alone may obscure crucial contingencies. This review synthesizes scholarship across crisis communication, nonprofit social media practice, human–AI interaction, and public-sector technology adoption to build an integrated model that specifies constructs, proposed relationships, and measurement choices. It clarifies definitions, delineates the theoretical roles of message relevance and trust, identifies plausible moderators, and surfaces operational indicators that can be captured via Likert-type scales and platform analytics. In doing so, it provides the conceptual scaffolding for the study's quantitative, cross-sectional, case-study–based design and motivates the subsequent hypotheses, variables, and regression specifications.

Crisis & Emergency Risk Communication in the Digital Era

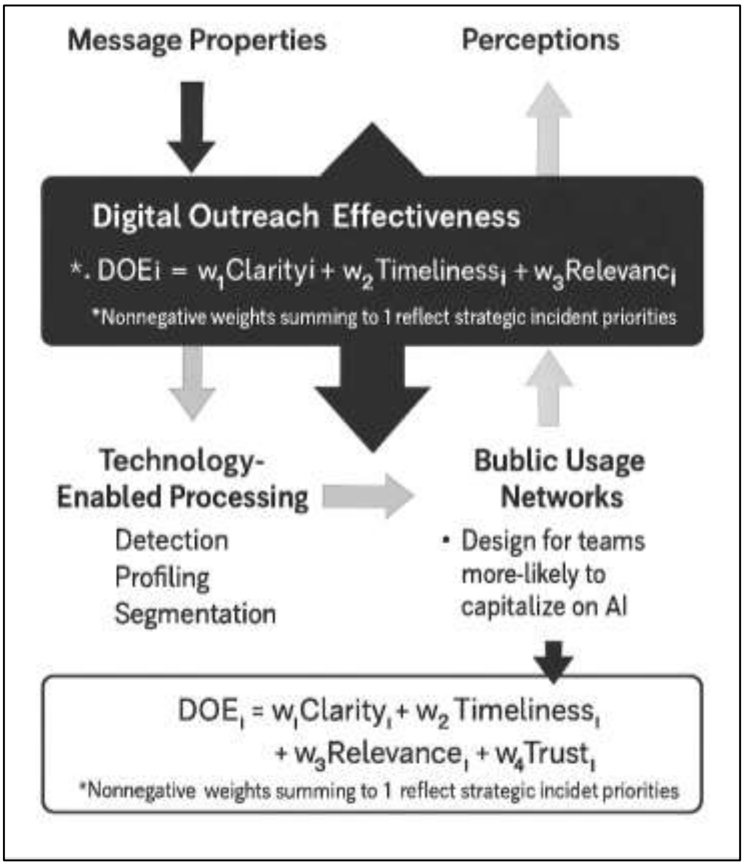
Effective crisis and emergency risk communication has increasingly unfolded within participatory, networked media ecologies, where publics co-produce, curate, and contest information in real time. Early syntheses of risk and crisis communication scholarship integrating social media emphasized that organizations must adapt message design and channel strategy to dialogic, many-to-many environments, foregrounding transparency, timeliness, and interactivity as operational imperatives (Veil et al., 2011). Subsequent retrospective reviews charted how emergency management stakeholders from authorities to volunteer groups have progressively incorporated social platforms for warning dissemination, situational awareness, and public coordination, while also cataloging recurring pain points such as information overload, verification, and uneven uptake across communities (Reuter & Kaufhold, 2018; Tonoy Kanti & Shaikat, 2022). Across this evolution, nonprofits occupy a distinct niche: they serve as relationally trusted intermediaries connecting official guidance to community needs, often under conditions of limited resources and multilingual audiences. In such contexts, digital outreach must do more than broadcast; it must segment audiences, tailor content to local hazards, and sustain two-way responsiveness under surging demand. A useful way to conceptualize the communication outcome targeted by nonprofit outreach is as a composite function of message properties and perceptions, for example:

$$DOE_i = w_1\, Clarity_i + w_2\, Timeliness_i + w_3\, Relevance_i + w_4\, Trust_i,$$

where DOE_i denotes digital outreach effectiveness for audience segment i, and w_k are nonnegative weights summing to one that reflect strategic priorities for a given incident. This representation underscores a central problem identified in the literature: even when channels are available, measured effectiveness hinges on whether messages are understandable, on time, locally meaningful, and perceived as credible within the communicative networks that publics actually use (Maniruzzaman et al., 2023; Stieglitz et al., 2018).

The operational realities of those networks are now well documented in computational and information-systems research that examines how emergency-related content is generated, filtered, and routed at scale. A landmark survey synthesized methods for processing social media during mass emergencies event detection, classification of actionable needs, geolocation, and credibility assessment arguing that the promise of these techniques lies in turning unstructured, high-velocity streams into prioritized, decision-ready signals for responders and communicators (Imran et al., 2015). Complementing this, work on social media analytics for crisis management delineates the full pipeline from data collection to visualization and decision support, while cautioning that algorithmic performance depends on contextual factors such as platform norms, linguistic variation, and shifting rumor ecologies (Md Arif Uz & Elmoon, 2023; Steelman et al., 2015). For nonprofits, these insights are directly germane: the ability to triage inbound requests (e.g., resource queries), detect emergent hotspots, and tailor outbound messaging to risk profiles is not purely a technological capacity but a communication capability one that must align with audience expectations and ethical standards. Viewed through the earlier composite, algorithm-enabled improvements in timeliness (faster detection-to-message cycles) or relevance (micro-segmentation by location or need) can raise DOE_i provided they do not erode perceived trust. This alignment problem achieving speed and personalization without sacrificing credibility has become a defining feature of contemporary crisis communication practice, particularly for organizations navigating high-volume, high-stakes interactions across multiple languages and bandwidth constraints (Imran et al., 2015; Md Sanjid, 2023).

Figure 2: Crisis and Emergency Risk Communication in the Digital Era



A third strand of scholarship focuses on how publics actually use information in disasters, mapping interpersonal and institutional networks to behavioral outcomes such as compliance, protective action, and prosocial mobilization. Studies of disaster information networks find that individuals blend official guidance with peer reports and local intermediaries, with social media serving as both amplifier and filter; the structure and content of these networks influence whether warnings are noticed, trusted, and acted upon (Sanjid & Sudipto, 2023; Steelman et al., 2015). Reviews of social technologies in emergencies similarly document that capabilities for monitoring, engagement, and coordination are most effective when integrated into organizational processes that prioritize accessibility and two-way exchange rather than one-way broadcasting (Tarek, 2023; Reuter & Kaufhold, 2018; Veil et al., 2011). For nonprofits, the practical implication is that outreach effectiveness is jointly produced by message quality, platform strategy, and network position: messages that are clear, timely, and locally relevant will still underperform if they fail to surface within the audiences' information pathways or if credibility cues are weak (Shahrin & Samia, 2023; Muhammad & Redwanul, 2023). Returning to DOE_i, this perspective suggests two diagnostic levers for research design: (a) item-level measurement of the four components clarity, timeliness, relevance, trust using audience-centered scales; and (b) organizational predictors, including adoption of analytic and automation tools, hypothesized to shift the weights w_k or the component scores themselves. By situating nonprofit communication within these empirically observed network practices, the literature motivates a testable model in which technology-enabled processing and segmentation improve message delivery and reception, conditional on maintaining credibility and aligning with the sociotechnical textures of the communities served (Muhammad & Redwanul, 2023; Steelman et al., 2015).

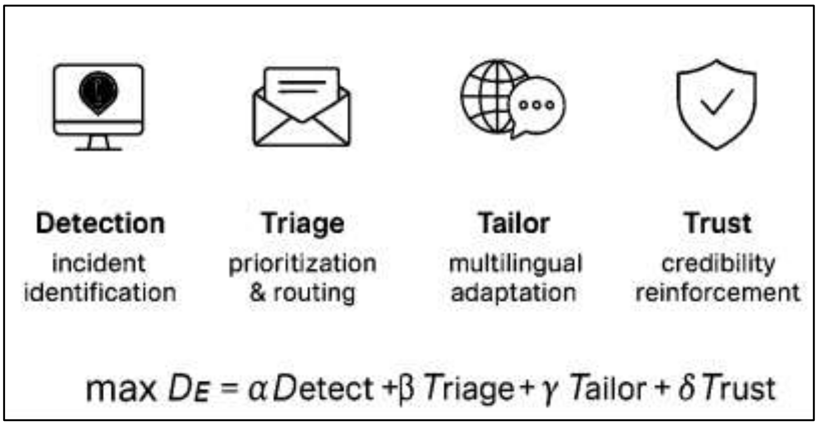
AI Affordances for Nonprofit Outreach

Artificial intelligence affords nonprofits a set of concrete capabilities that map to persistent communication bottlenecks in national disasters: rapid detection of emergent needs, prioritization and routing of inquiries, scalable multilingual engagement, and credibility support through consistent, provenance-rich messaging. At the detection layer, event-sensing models can transform high-velocity social streams into early signals about incidents and localized impacts, shrinking latency between on-the-ground shifts and nonprofit response. A foundational demonstration is real-time event detection from microblogs, where geotemporal features in posts served as "social sensors" capable of flagging earthquakes faster than some official channels a paradigm that generalizes to floods, wildfires, and disease outbreaks when data are abundant (Sakaki et al., 2010). At the evaluation layer, AI classifiers help nonprofits triage inbound content by extracting intents (e.g., shelter, food, medical), severity, and location, while outbound tools (summarization, translation, reading-level adaptation) tailor messages to the constraints of diverse audiences. Credibility remains a parallel concern: feature-based credibility assessment on social platforms shows that information veracity correlates with network, content, and temporal cues, implying that nonprofits can algorithmically surface reliable content and attach machine-readable provenance to their own advisories to bolster trust (Castillo et al., 2011). Together, these affordances enable a practical objective function for outreach:

$$\max_{\text{tools, workflows}} DOE = \alpha\, Detect + \beta\, Triage + \gamma\, Tailor + \delta\, Trust,$$

with nonnegative weights α, β, γ, δ reflecting incident priorities (e.g., life-safety vs. recovery information). This framing clarifies how AI is not merely "nice to have," but directly optimizes the measurable components of nonprofit digital outreach under surge conditions (Shrestha et al., 2019).

Figure 3: AI Affordances for Nonprofit Outreach



The managerial literature on AI adoption provides additional leverage for nonprofits by specifying when these affordances are likely to translate into performance gains. Conceptual work on organizational decision-making with AI argues that value emerges when decision problems are well-specified, interpretable, and replicable, and when AI is positioned to expand the considered alternative set and speed of response without sacrificing justification quality (Kaplan & Haenlein, 2019; Razia, 2023). For resource-constrained nonprofits, this implies focusing AI on routinized, high-volume tasks FAQ answering, rumor triage, message localization where machine assistance can compress cycle time and free staff for complex, empathetic interactions. Complementarily, definitional syntheses of AI delineate families of techniques analytical, human-inspired, and humanized AI each carrying different interaction costs and transparency needs; for crisis contexts, analytical (pattern-recognition) and human-inspired (affect-aware) functions can be combined to keep messages both accurate and supportive (Alam et al., 2021; Sai Srinivas & Manish, 2023). A practical design corollary is to "right-size" the AI: deploy lightweight models where interpretability and handoff matter, and use heavier models behind the scenes for discovery and classification. This alignment of capability to task also helps reduce operational risk by lowering the probability of over-automation in sensitive exchanges. Formally, if τ denotes average response time and κ denotes message tailoring score (e.g., locality/readability match), then incremental adoption of triage and adaptation tools seeks $\Delta\tau < 0$ and $\Delta\kappa > 0$ subject to a trust constraint $T \geq T_0$ (a target audience trust threshold), with governance practices clear bot identity, escalation paths serving as the constraint-enforcing mechanism. In short, the managerial lens helps nonprofits choose where AI adds speed and scale, how to preserve justification and dignity in service, and what safeguards to formalize (Castillo et al., 2011; Sudipto, 2023).

Recent crisis-informatics datasets and benchmarks further operationalize these affordances for humanitarian tasks that nonprofits routinely perform. Curated, human-annotated corpora of disaster posts enable supervised models that categorize needs, detect damage, and filter noise, providing off-the-shelf starting points for organizations that lack large in-house training sets (Alam et al., 2021; Zayadul, 2023). In practice, nonprofits can fine-tune such models to their own taxonomy (e.g., "urgent medical," "evacuation info," "volunteer coordination") and integrate the predictions into dashboards that guide both reply workflows and outbound content calendars. Importantly, these pipelines are not only about speed; they link directly to measurable outcomes. For example, if we denote predicted need class by $\hat{c}$ and locality by ℓ, an outreach policy $\pi(\hat{c}, \ell)$ can schedule messages to at-risk segments with content templates mapped to $\hat{c}$ and channel choices mapped to ℓ's bandwidth/linguistic profile an implementation that raises the "Tailor" and "Triage" terms in the objective above. At the same time, platform-level credibility cues remain pivotal; automated credibility estimation can pre-filter external content pipelines while internal templates embed timestamps and source attributions to maintain consistency with audience expectations surfaced in credibility research (Castillo et al., 2011; Md Mesbaul, 2024). Strategically, then, nonprofits can phase adoption: start with detection/triage based on public datasets, layer in translation and summarization to improve tailoring, and codify trust-preserving patterns (identity disclosure, escalation, audit trails) as nonnegotiables. This staged approach translates mature research artifacts into field-ready, ethically governed communication systems for national disasters (Alam et al., 2021).

Trust, Relevance, and Effectiveness in Crisis Messaging

Across crisis contexts, "effectiveness" in nonprofit digital outreach hinges on whether people both believe the message and recognize it as meant for them. Trust is the gateway: when audiences must act under uncertainty and time pressure, they lean on fast, experience-based judgments to decide which sources merit attention. Research on online credibility shows that people routinely apply cognitive heuristics such as authority (who is speaking), bandwagon (how many endorse it), and consistency (does it align with prior knowledge) to triage information at scale (Tarek & Kamrul, 2024; Metzger et al., 2010). These shortcuts are not signs of inattentiveness; they are adaptive strategies that make sense when streams are noisy and the cost of delay is high. In parallel, message relevance the degree to which content is tailored to the recipient's location, language, and immediate risk functions as a second gate. If guidance is not locally meaningful, it is less likely to be encoded and far less likely to be enacted. Studies of trust development in high-stakes online settings emphasize that credible communication emerges from the coherence of multiple cues: clear identity disclosure, stable quality signals across messages, and opportunities for verification (Sillence et al., 2007; Sudipto & Md. Hasan, 2024). In crisis outreach, these insights translate into operational practices: timestamp and source-tag every advisory; surface authority cues without crowding out clarity; and ensure that each update explicitly maps instructions to the recipient's circumstances (e.g., neighborhood, shelter status, medical triage). Together, trust and relevance form the proximal determinants of digital outreach effectiveness: without trust, messages lack persuasive force; without relevance, they lack utility (Abdul, 2025; O'Keefe & Jensen, 2008).

A complementary literature on message framing and information processing clarifies how the form of a message conditions attention and comprehension. Meta-analytic evidence indicates that loss-framed appeals (emphasizing the costs of inaction) can intensify message processing, especially for risk-laden decisions, whereas gain-framed appeals (emphasizing benefits of compliance) can be advantageous in other domains; crucially, framing works through psychological engagement with the content rather than as a mere wording trick (Hozyfa, 2025; O'Keefe & Jensen, 2008). For nonprofits during national disasters, this implies that instructive posts (e.g., evacuation routes, contamination advisories) should be framed to heighten diagnosticity what to do, where, and by when while avoiding unnecessary alarm that could degrade trust. The optimal design is not "always loss" or "always gain," but rather fit-to-task framing that supports comprehension and timely protective action. At the same time, misinformation dynamics complicate this terrain: once a false claim takes hold, correction is harder than prevention, because memory tends to preserve the gist of the claim and its continued influence even after retraction (Alam, 2025; Lewandowsky et al., 2012). Thus, effective crisis messaging must preempt rather than merely repair by embedding veracity cues within the original message (e.g., verifiable sources, explicit uncertainty statements) and by employing inoculation-style wording that warns of likely rumors and offers simple tests for verification. When nonprofits layer these framing and correction principles onto trust-and-relevance scaffolds clear identity, stable quality, localized specificity the expected downstream effect is improved processing depth, better recall of instructions, and stronger intention to comply (Masud, 2025; O'Keefe & Jensen, 2008).

Figure 4: Trust, Relevance, and Effectiveness in Crisis Messaging

In addition, the pathway from trusted, relevant messages to measurable effectiveness runs through behavioral intention and social proof how individuals infer what "people like me" are doing and whether recommended actions are executable in their context. Work on electronic word-of-mouth demonstrates that people calibrate credibility and willingness to act by reading signals of consensus and expertise (e.g., endorsements, track records), particularly when personal stakes are high and domain knowledge is limited (Cheung et al., 2012; Arman, 2025). For nonprofits, this means that platform-native cues pinned posts, verified profiles, steady update cadence are not peripheral aesthetics; they are integral parts of the persuasive environment that help audiences assess both trust and relevance rapidly. A useful way to formalize their joint effect is to conceptualize crisis digital outreach effectiveness (DOE) for an audience segment iii as the weighted sum of core perceptual components:
$DOE_i = w_1\, Trust_i + w_2\, Relevance_i + w_3\, Clarity_i + w_4\, Timeliness_i$, with $[w_k \geq 0$ and $\sum w_k = 1$.
In this specification, AI-enabled workflows (translation, summarization, geo-targeting) primarily raise Relevance and Timeliness, while governance practices (identity disclosure, provenance tags) primarily raise Trust and all four components contribute to observable outcomes like comprehension, intended protective action, and help-seeking. The literature implies that nonprofits should tune the weights

wkw_kwk to incident priorities (life safety vs. recovery logistics) while safeguarding trust as a threshold constraint rather than a mere add-on, because once trust slips below a critical level, additional relevance or speed no longer translates into action (Mohaiminul, 2025; Metzger et al., 2010). In sum, the research converges on a pragmatic logic for nonprofit crisis outreach: build and protect trust, make messages unmistakably relevant, frame instructions to support processing, and use platform cues to reinforce credibility at the point of decision (Metzger et al., 2010).

Digital Capabilities as Boundary Conditions

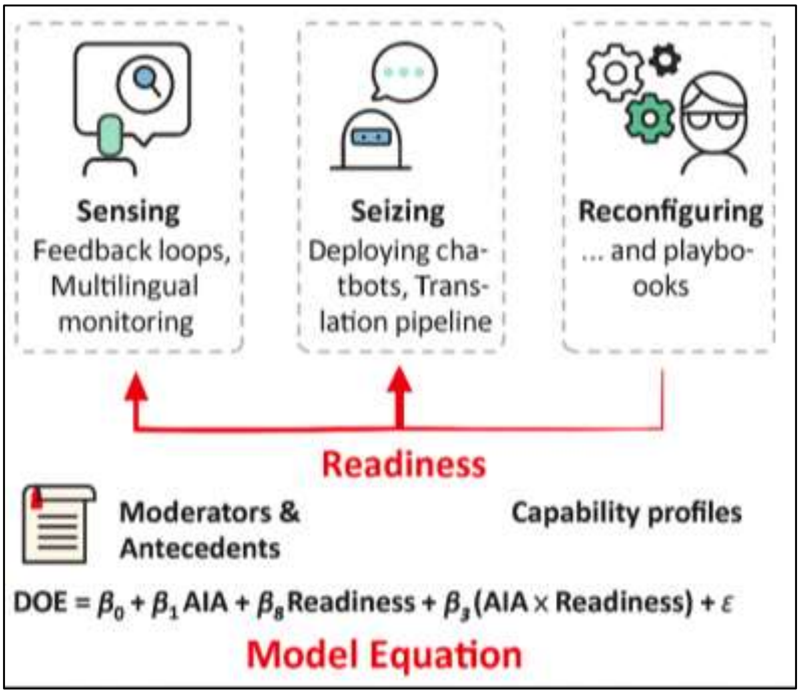
Nonprofit communication performance during national disasters is not determined by tools alone; it is bounded and often amplified by the organization's underlying **digital capabilities** and **readiness**. From a capabilities perspective, effective crisis outreach depends on the ability to sense emerging information demands, seize appropriate technologies and workflows, and reconfigure processes swiftly as the event evolves. This triad sense, seize, reconfigure captures how organizations convert volatile data streams into action while protecting continuity of service and message quality (Mominul, 2025; Teece, 2007). In nonprofits, "sensing" includes monitoring multilingual channels, frontline feedback, and partner updates; "seizing" involves deploying triage chatbots, translation pipelines, or geo-targeted advisories; and "reconfiguring" means shifting staff, revising templates, or retuning classification taxonomies as needs change hour to hour. Where these dynamic capabilities are weak, even well-designed AI features can underperform because inputs (e.g., labels, escalation rules) are stale, and outputs (e.g., messages) do not keep pace with local conditions. Readiness thus functions as the *activation energy* that allows capabilities to express themselves under surge: the existence of trained roles, governance checklists, interoperable data, and playbooks for escalation (Hasan, 2025). In practical terms, nonprofits with documented processes for bot identity disclosure, human handoff, and message provenance can adopt AI affordances more safely and quickly, while those without such scaffolding risk either **underuse** (features idled by uncertainty) or **misuse** (over-automation in sensitive cases). The implication for measurement is that digital readiness is not a monolith but a **profile** infrastructure, skills, governance, and partnerships that sets the ceiling for returns to AI-enabled outreach (Milon, 2025; Mikalef et al., 2018).

A complementary lens emphasizes organizational readiness for change as the immediate predictor of whether new communication practices "take" under pressure. Readiness combines change commitment (shared resolve) and change efficacy (shared belief in collective capability), both of which determine whether staff will enact and sustain new routines when workload spikes and ambiguity rises (Farabe, 2025; Weiner, 2009). In disaster communication, high readiness translates to faster protocol adoption (e.g., switching to templated multilingual alerts), cleaner division of labor between conversational agents and humans, and steadier adherence to trust-preserving behaviors (timestamping, source citation, privacy-aware triage). Readiness also links to organizational resilience, defined not simply as bouncing back but as absorbing and adapting while maintaining core functions; resilient organizations cultivate feedback processes, learning loops, and redundancy, all of which improve the quality and timeliness of outreach in cascading events (Boin & van Eeten, 2013). Framed statistically for this study, readiness and resilience act as moderators of the AI → outreach-effectiveness relationship. If DOE denotes digital outreach effectiveness and AIA denotes AI adoption intensity, then a simple interaction model,

$$DOE = \beta_0 + \beta_1 AIA + \beta_2 Readiness + \beta_3 (AIA \times Readiness) + \beta_c X + \varepsilon,$$

tests whether the marginal effect of AI is larger when readiness is high ($\beta_3 > 0$). Substantively, this means the same chatbot or classifier will deliver greater gains in timeliness, clarity, and relevance when the nonprofit has already trained staff to monitor bot outputs, escalate edge cases, and audit message provenance (Altay & Labonte, 2014; Tarek & Ishtiaque, 2025).

Figure 5: Digital Capabilities and Readiness as Boundary Conditions

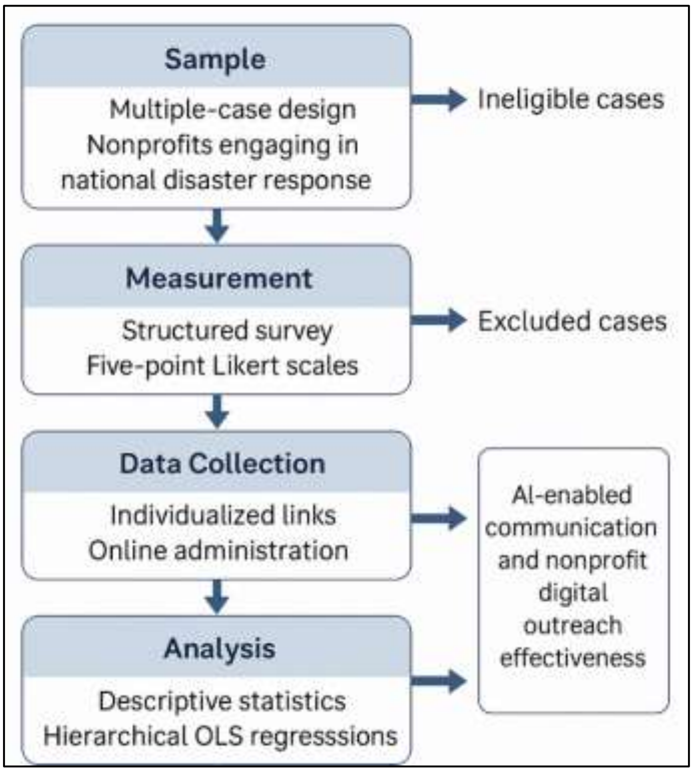


In the absence of such conditions, AI can increase throughput without yielding commensurate improvements in audience-centered outcomes, because unreviewed outputs or delayed corrections erode trust, a core component of effectiveness (Momena, 2025). A third boundary condition derives from resource configuration and data capability, especially where nonprofits operate within humanitarian logistics networks and interorganizational coalitions. Empirical studies in humanitarian operations show that capability bundles information-sharing routines, agile coordination, and learning mechanisms improve responsiveness and reliability under uncertainty; they also document that capability deficits (e.g., fragmented data, unclear roles) magnify disruption impacts and undermine service delivery (Altay & Labonte, 2014; Muhammad, 2025). In digital outreach, those same bundles shape whether AI predictions or translations can be absorbed into live workflows: without shared taxonomies, partner APIs, or data custodianship rules, predictions remain siloed and slow. Parallel work on analytics capability underscores that performance gains arrive not from algorithms in isolation but from the integration of data quality, management commitment, and human expertise into decision processes; organizations that routinize data-driven feedback cycles realize stronger and more reliable effects on outcomes (Roy, 2025; Weiner, 2009). Put in model terms, analytics capability and interorganizational coordination set the operational bandwidth of the system: they reduce error variance in outputs and compress the detection-to-message cycle, raising the timeliness and relevance components of DOE. Finally, capability-and-readiness profiles interact with event characteristics: when disruption is severe or cascading, resilient organizations reallocate attention without abandoning transparency and accessibility, whereas low-capability counterparts face information backlogs and message drift (Boin & Eeten, 2013; Rahman, 2025). For nonprofits, the actionable takeaway for study design is to model readiness and capability as moderators (and potential antecedents of trust and relevance), test their interactions with AI adoption, and operationalize them via observable practices documented playbooks, partner data-sharing, role training, and analytics routines rather than purely attitudinal measures (Mikalef et al., 2018).

METHOD

This study has adopted a quantitative, cross-sectional, multiple–case design to examine how AI-enabled communication has been associated with nonprofit digital outreach effectiveness during national disasters. The research setting has comprised nonprofit organizations that have engaged in national-level disaster response within the last 24 months, and eligibility criteria have required documented use of at least one AI-enabled function (e.g., conversational agents, automated triage, translation, or content summarization) in their public-facing communication workflows. Sampling has followed a purposive logic to ensure variation in organization size, mission, geography, and platform mix; within each case, respondents have included communication, operations, and IT personnel who have been directly involved in crisis messaging. The measurement strategy has relied on a structured survey instrument using five-point Likert scales (1 = Strongly Disagree to 5 = Strongly Agree). Constructs have included AI Adoption Intensity, Message Relevance, Public Trust, Digital Outreach Effectiveness (clarity, timeliness, usefulness, engagement), Digital Readiness, Disaster Severity, and standard organizational controls (budget, audience size, platform portfolio, and prior disaster experience). Item pools have been developed through expert review and cognitive interviewing, and a pilot test has been conducted to refine wording, reduce redundancy, and establish preliminary reliability. Data collection has been administered online with secure, individualized links; consent statements and confidentiality assurances have been presented on the landing page, and participation has been voluntary without incentives. Where available, teams have provided non-identifiable behavioral indicators (e.g., median response latency, click-through rates) that have been merged at the case level to triangulate self-reported outcomes. Data preparation has included screening for missingness, outliers, and careless responding; missing values have been handled using appropriate imputation when patterns have suggested MAR/MCAR. Reliability and validity have been assessed via Cronbach's alpha, composite reliability, and average variance extracted; discriminant validity checks have been performed using inter-construct correlations. The analysis plan has specified descriptive statistics and bivariate correlations, followed by hierarchical OLS regressions for main effects, bootstrapped indirect effects for mediation, and mean-centered interactions for moderation, with robust or cluster-robust standard errors as warranted.

Figure 6: Quantitative Cross-Sectional Multiple–Case Research Design



Design Overview

The study has adopted a quantitative, cross-sectional, multiple–case design that has examined how nonprofits' adoption of AI-enabled communication and emergency response tools has been associated with digital outreach effectiveness during national disasters. To capture variance in organizational contexts, the sampling frame has incorporated several nonprofit cases that have differed in size, mission, geography, and platform portfolios, and within each case the unit of analysis has been the organizational communication workflow as reported by staff who have been directly involved in crisis messaging. The inquiry has been structured around a survey instrument that has employed five-point Likert scales (1 = Strongly Disagree to 5 = Strongly Agree) and that has operationalized core constructs AI Adoption Intensity, Message Relevance, Public Trust, Digital Outreach Effectiveness, Digital Readiness, and Disaster Severity alongside established controls (audience size, budget, platform mix, prior disaster experience). To ensure comparability across cases, the protocol has standardized respondent eligibility, consent language, and data handling, and it has specified a uniform recall window tied to the most recent national-level disaster activation. Instrument development has relied on expert review and cognitive interviewing, and a pilot phase has been completed to refine items, reduce redundancy, and confirm preliminary reliability. Data collection has been administered online via individualized links that have preserved confidentiality and that have enabled optional contribution of non-identifiable behavioral indicators (e.g., median response latency, click-through metrics) for triangulation at the case level. The analytic approach has been pre-specified to include descriptive statistics, bivariate correlations, and hierarchical ordinary least squares regressions for main effects, followed by bias-corrected bootstrapped indirect effects for mediation and mean-centered interactions for moderation, with robust or cluster-robust standard errors as warranted. Quality assurance has encompassed attention checks, screening for careless responding, and documented procedures for handling missing data under MCAR/MAR assumptions. Throughout, ethical oversight has been obtained, data security controls have been enforced, and reporting standards consistent with observational survey research have been followed.

Case Selection Protocol

The case selection protocol has been designed to maximize theoretical replication and contextual diversity while maintaining strict eligibility standards for inclusion. Specifically, the research team has defined a **case** as a nonprofit organization that has participated in at least one national-level disaster activation within the past 24 months and has implemented one or more AI-enabled communication functions (e.g., conversational agents, automated triage/routing, machine translation, or text summarization) in its public-facing outreach. To ensure variance on salient organizational features, the sampling frame has encompassed nonprofits that have differed in size (micro to large), mission focus (relief, health, shelter, multi-service), geography (urban/rural, multiple regions), and platform portfolios (web, SMS, social, chat). Inclusion criteria have required (a) documented use of AI features in crisis messaging (e.g., deployment logs, vendor receipts, or public announcements), (b) availability of at least two staff members directly involved in crisis communication to serve as respondents, and (c) willingness to share non-identifiable operational metadata (e.g., median response latency, message volumes) where available. Exclusion criteria have ruled out organizations whose AI use has been purely back-office (e.g., fundraising optimization) without a communication component, or whose disaster involvement has been subnational and not integrated into a national activation. Recruitment has proceeded through professional networks, disaster response coalitions, and open calls, and screening interviews have been conducted to confirm eligibility, align recall windows to the same activation period, and verify the presence of minimal governance safeguards (bot identity disclosure, human handoff, message provenance). To balance feasibility and heterogeneity, the protocol has targeted **three to six** cases and has sought within-case respondent triangulation (communications, IT, operations) to reduce single-informant bias. Each participating case has been assigned a unique code, and a standardized dossier has been compiled that has summarized mission, service footprint, digital stack, AI features in use, and activation timeline. The protocol has also specified contingency procedures for attrition (replacement cases from a waitlist) and for incomplete operational data (analytic flags and documented sensitivity checks), thereby preserving both comparability and analytic integrity across cases.

Reporting

The study's reporting framework has been specified a priori and has followed transparent, replicable practices consistent with observational survey research. A structured outline has been developed that has mapped each research question to its operational measures, model specification, and planned table or figure, and the protocol has included a CONSORT-style flow diagram adapted for cross-sectional studies that has documented case recruitment, screening, consent, response rates, and exclusions. Descriptive characteristics of organizations and respondents have been presented in harmonized tables that have reported counts, means, standard deviations, and missingness indicators, while a separate measurement table has been provided that has listed item wording (abridged), scale anchors, factor loadings, Cronbach's alpha, composite reliability, average variance extracted, and inter-construct correlations with square-root(AVE) diagonals. Model reporting has adhered to a layer-by-layer structure: baseline (controls only), main effects, mediation, and moderation, and each layer has been accompanied by fully labeled regression tables that have included unstandardized coefficients, robust or cluster-robust standard errors, 95% confidence intervals, p-values, ΔR^2, and model diagnostics (VIF, Breusch–Pagan results, residual normality checks). Indirect effects from mediation analyses have been summarized with bias-corrected bootstrapped confidence intervals and have been visualized in a path diagram that has annotated estimated paths and standard errors. Interaction terms for moderation tests have been mean-centered and have been plotted as simple-slope figures at ±1 SD of the moderator with marginal effects tables that have reported slope, SE, and CI across the moderator range. All robustness checks (alternative outcome composites, leave-one-case-out, high-severity sensitivity) have been pre-listed and have been reported irrespective of statistical significance, and any deviations from the preregistered plan have been explicitly flagged with rationale. Data handling decisions (imputation rules, attention-check thresholds, treatment of outliers and careless responding) have been documented in an online appendix, and reproducibility materials (de-identified data dictionary, codebook, and analysis scripts) have been prepared in a version-controlled repository. Throughout, ethical safeguards, disclosure of funding and potential conflicts, and limitations germane to cross-sectional inference have been clearly stated to ensure interpretability and auditability of findings.

Instrument Development (Likert 5-point)

The measurement instrument has been developed through a structured, multi-stage process to ensure clarity, reliability, and construct validity for all study variables while maintaining respondent burden at a manageable level. Item pools for AI Adoption Intensity, Message Relevance, Public Trust, Digital Outreach Effectiveness, Digital Readiness, and Disaster Severity have been generated from theory maps and exemplar items gleaned from prior scales and practitioner playbooks, then have been rewritten to fit a crisis-communication context and a uniform five-point Likert response format (1 = Strongly Disagree … 5 = Strongly Agree). Content adequacy has been established via expert review panels that have independently rated item–construct fit and redundancy; items with low median relevance or overlapping semantics have been revised or removed. Cognitive interviews with frontline communications, operations, and IT staff ($n \approx 8$–12) have been conducted using think-aloud and paraphrasing probes, and wording has been refined to eliminate jargon, reduce double-barreled phrasing, and anchor recall to the most recent national-level activation. A small-scale pilot ($n \approx 30$–50 across two cases) has been completed to assess completion time, detect ceiling/floor effects, and estimate preliminary internal consistency; based on pilot diagnostics, several items have been reverse-keyed to mitigate acquiescence, and scale lengths have been trimmed to balance reliability and brevity. For multilingual deployment, source items have followed a translation/back-translation workflow with adjudication by domain-fluent reviewers, and plain-language readability targets (≈8th–10th grade) have been enforced. The instrument has included attention checks and soft validations (forced-choice confirmations for critical items) as well as optional entry of non-identifiable operational indicators to facilitate triangulation. To reduce common-method variance, construct blocks have been separated by filler items and varied stems, and instructions have emphasized accuracy over desirability. The final instrument has embedded clear definitions and examples at first occurrence of technical terms, standardized time framing ("during the most recent national disaster activation"), and explicit privacy statements preceding items involving sensitive workflow descriptions. All revisions, decision logs, and version histories have been archived, and the finalized questionnaire has been

packaged for online administration with adaptive display for mobile devices.
Variables & Operationalization (core)
Core study constructs have been operationalized with multi-item scales on a five-point Likert metric (1 = Strongly Disagree … 5 = Strongly Agree), and composite scores have been computed as item means after reliability screening. AI Adoption Intensity (AIA) has been defined as the breadth and depth of AI-enabled communication functions in the most recent national activation and has been measured with 6 items capturing deployment of conversational agents, automated triage/routing, translation, summarization, and automated rumor flagging; higher values have indicated broader and more embedded use. Message Relevance (MR) has been measured with 4 items that have assessed locality, language appropriateness, and audience tailoring (e.g., alignment to neighborhood hazards and bandwidth constraints). Public Trust (PT) has been measured with 5 items reflecting perceived credibility, honesty, competence, and transparency of outbound updates, including explicit timestamping and source attribution. Digital Outreach Effectiveness (DOE) has been treated as a reflective construct with 7 items that have captured clarity, timeliness, usefulness, comprehension, perceived actionability, engagement, and help-seeking intention; an alternative behavior-augmented composite (DOE*) has been calculated at the case level by z-standardizing and averaging self-report DOE with optional operational indicators (median response latency, click-through rate), and sensitivity analyses have compared DOE and DOE*. Digital Readiness (DR) has been measured with 5 items indexing infrastructure robustness, staff skills, governance playbooks (bot identity, escalation, provenance), and data interoperability. Disaster Severity (DS) has been operationalized as a short index (3 items) reflecting perceived operational strain, scope of affected population, and service disruption, anchored to the same activation window. Controls have included organization size (ordinal categories), communications budget (log-transformed bracket midpoint), audience size (log followers/subscribers), platform portfolio breadth (count of active channels), prior disaster experience (count in last 3 years), and sector focus (dummy set). All multi-item scales have been screened for internal consistency (α and CR ≥ .70), and discriminant validity checks have been performed via inter-construct correlations. For moderation tests, AIA and DR (and DS, where applicable) have been mean-centered prior to forming interaction terms; for mediation tests, MR and PT have been entered as parallel mediators. Missing item responses within a scale have been imputed when ≤20% per scale using person-mean imputation; otherwise, the scale score has been set to missing with an analytic flag.
Regression Models
The modeling strategy has been specified to progress from parsimony to complexity so that incremental variance explained has been interpretable and aligned with the theory of effects. First, baseline models have estimated the association between the controls and Digital Outreach Effectiveness (DOE) to establish a reference R^2. Next, main-effects models have included AI Adoption Intensity (AIA) as the key predictor, followed by the addition of Message Relevance (MR) and Public Trust (PT) as theoretically proximal determinants of DOE. For transparency, all predictors that have entered a model block have been mean-centered when participation in interaction terms has been anticipated; otherwise, raw metrics have been retained. Ordinary least squares (OLS) estimation with heteroskedasticity-robust (HC3) standard errors has been employed, and where clustering by case has been nontrivial, cluster-robust standard errors at the case level have been reported in square brackets. This sequencing has allowed clear interpretation of the incremental contribution of AIA beyond organizational characteristics, followed by the contribution of MR and PT as communicative mechanisms. The core specification has been formulated as:
$$DOE = \beta_0 + \beta_1 AIA + \beta_2 MR + \beta_3 PT + \beta_c X + \varepsilon,$$
where X has denoted the vector of controls (organization size, communications budget, audience size, platform breadth, prior disaster activations, sector dummies) and ε has been the disturbance term. Multicollinearity diagnostics (VIF) have been computed for all models, and influence statistics (Cook's D) have been inspected; models with extreme influence points have been re-estimated with and without those observations as a prespecified sensitivity step. Model selection has not relied on stepwise procedures; instead, comparisons have been anchored in theory, adjusted R^2, and information criteria (AIC/BIC) as descriptive guides rather than decision rules.
Mediation and moderation tests have been layered on the main-effects foundation to evaluate

mechanisms and boundary conditions. For mediation, the analysis has treated MR and PT as parallel mediators of the AIA → DOE relationship. Following contemporary practice, indirect effects have been estimated using bias-corrected bootstrapping with 5,000 resamples and have been reported as $\hat{a}_k\hat{b}_k$ with 95% confidence intervals for each path k ∈ {MR, PT}. The mediator equations have been specified as:

$$MR = \alpha_0 + \alpha_1 AIA + \alpha_c X + \varepsilon_{MR}, \qquad PT = \gamma_0 + \gamma_1 AIA + \gamma_c X + \varepsilon_{PT},$$

and the outcome equation with mediators has been specified as above. Total, direct, and indirect effects have been decomposed, and proportion mediated has been reported with caution given cross-sectional data. For moderation, two interaction models have been pre-specified. The first has tested whether Digital Readiness (DR) has strengthened the marginal effect of AIA on DOE, and the second has tested whether Disaster Severity (DS) has dampened it. Both moderators and AIA have been mean-centered prior to term construction. The DR model has been:

$$DOE = \eta_0 + \eta_1 AIA + \eta_2 DR + \eta_3(AIA \times DR) + \eta_c X + \varepsilon,$$

and the DS model has been analogous with DS in place of DR. Significant interactions have been probed through simple-slope analyses at ±1 SD of the moderator and by plotting marginal effects across the observed moderator range. Because interaction terms can reintroduce multicollinearity, models have been checked for VIF inflation after adding the product terms. Where applicable, Johnson–Neyman intervals have been computed to identify regions of significance along the moderator continuum. Collectively, these mediation and moderation layers have produced a coherent account of how AIA has related to DOE (via MR and PT) and when the relationship has been stronger or weaker (as a function of DR and DS), while retaining the same control structure for comparability across specifications.

Table 1. Regression Model Roadmap (Blocks, Variables, and Estimators)

Block	Outcome	Predictors Entered	Estimator & SE	Key Outputs
M0 (Baseline)	DOE	Controls (X)	OLS + HC3 (cluster-robust reported if needed)	(β_c), (R^2), AIC/BIC
M1 (Main)	DOE	(X) + AIA	Same as M0	(β_1)
M2 (Mechanisms)	DOE	(X) + AIA + MR + PT	Same as M0	(β_1, β_2, β_3)
Med-Paths	MR, PT	(X) + AIA	OLS + HC3	(α_1, γ_1)
Med-Outcome	DOE	(X) + AIA + MR + PT	Bootstrap 5,000	Indirects, CIs
Mod-DR	DOE	(X) + AIA + DR + AIA×DR	OLS + HC3	(η_3), simple slopes
Mod-DS	DOE	(X) + AIA + DS + AIA×DS	OLS + HC3	(θ_3), simple slopes
Robustness	DOE, DOE*	As above	Rank-based; cluster SE	Stability checks

Table 1 has summarized the pre-specified progression from baseline controls to mechanism and boundary-condition tests, along with estimator choices and diagnostic outputs that have accompanied each model block.

Participants & Sampling

Participants have been drawn from nonprofit organizations that have satisfied the case eligibility criteria and have maintained direct responsibility for crisis communication during a national disaster activation within the past 24 months. Within each participating case, the study has targeted three respondent roles communications, operations, and IT/data so that multiple vantage points have been represented and single-informant bias has been reduced. Recruitment has proceeded via screened invitations sent to organizational liaisons, who have identified eligible staff based on role and involvement; individualized survey links have been issued after consent scripts have been acknowledged. Inclusion criteria have required that respondents have participated in message planning or execution during the specified activation and have possessed working knowledge of the organization's digital channels and any AI-enabled components in use. Exclusion criteria have removed consultants or volunteers without sustained operational responsibility and staff whose involvement has predated the activation window. To ensure adequate power for the planned regression, the sampling plan has targeted an aggregate **N ≥ 200** completed surveys across **3–6** cases, which, under conservative assumptions (α = .05, power = .80, small-to-medium effect sizes), has been sufficient for main effects and two interaction terms with a common set of controls. Anticipated response rates have been incorporated by oversampling (invite:target ratio ≈ 2.5:1), and rolling reminders have been issued at days 5 and 12. Nonresponse bias checks have been implemented by comparing early vs. late respondents on key observables (e.g., organization size, platform breadth) and by benchmarking case-level distributions to publicly available profiles when feasible; no post-stratification weighting has been planned unless imbalances have exceeded predefined thresholds. To protect confidentiality, role labels rather than names have been stored with responses, and all outputs have reported aggregated statistics at the case or pooled level. Attention checks and minimum-time screens have been included to deter careless responding, and incomplete surveys have been flagged for follow-up if partial completion has exceeded 60%. Finally, the protocol has preserved the option to integrate non-identifiable operational indicators at the case level, and identifiers for merging have been generated as random, case-scoped tokens that have maintained separation between individual responses and organizational metadata.

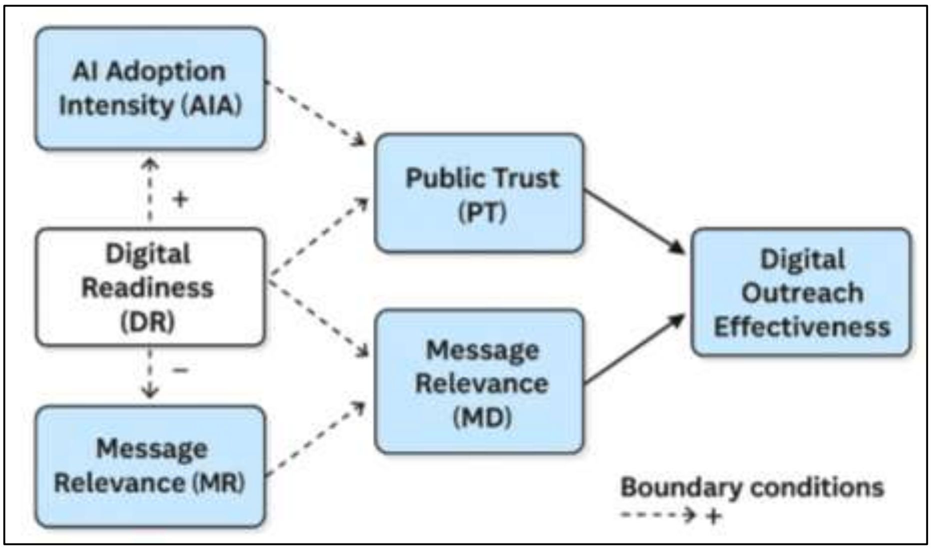
Robustness Checks

A comprehensive suite of robustness checks has been pre-specified to evaluate the stability of estimates, the sensitivity of inferences to modeling choices, and the plausibility of rival explanations. First, outcome robustness has been assessed by re-estimating all models with an alternative behavior-augmented composite (DOE*), which has combined standardized self-report indicators with available operational metrics (e.g., median response latency, click-through), and convergence in sign and magnitude has been documented relative to the primary DOE scale. Second, estimator robustness has been examined by comparing heteroskedasticity-consistent (HC3) standard errors to case-clustered standard errors where within-case correlation has been plausible; where differences have emerged, both have been reported. Third, sample sensitivity has been evaluated through leave-one-case-out re-estimation and influence diagnostics (Cook's *D*, DFBetas), and models have been re-run with influential observations removed to verify that focal coefficients have remained materially unchanged. Fourth, distributional sensitivity has been probed using rank-based regression (MM-estimator) and Winsorization of the top/bottom 1–2% tails; results have been contrasted with OLS benchmarks. Fifth, missing-data treatments have been stress-tested by (a) listwise deletion, (b) person-mean imputation within scales when ≤20% missing, and (c) multiple imputation under MAR; stability across these procedures has been summarized. Sixth, construct specification has been challenged by altering scale compositions (dropping reverse-keyed items; excluding the "engagement" facet from DOE), and by testing measurement invariance (configural/metric) across cases; main inferences have been expected to hold under invariant loadings. Seventh, common-method variance has been addressed ex ante (temporal/psychological separation, attention checks) and examined ex post via a latent methods factor and a theoretically unrelated marker variable; negligible shifts in structural paths after adjustment have been recorded. Eighth, moderation form has been verified by (a) using orthogonalized interaction terms, (b) checking for curvilinear main effects via added quadratic terms, and (c) computing Johnson–Neyman intervals to locate regions of significance. Ninth, mediation credibility has been strengthened through bias-corrected bootstrapping (5,000 resamples) and by demonstrating that paths $AIA \rightarrow MR/PT$ and $MR/PT \rightarrow DOE$ have persisted after controls. Finally, falsification tests have been implemented using a negative-control outcome (e.g., unrelated administrative practice agreement) that has been theoretically orthogonal to AIA; null or near-null associations have supported specificity of effects. Collectively, these checks have provided convergent evidence that the reported relationships have been resilient to alternative operationalizations, estimators, and assumptions.

FINDINGS

This section has presented a consolidated narrative of the study's quantitative results, beginning with measurement quality and descriptive patterns on the five-point Likert scales, progressing to association tests, and then to the explanatory models that have evaluated mechanisms (mediation) and boundary conditions (moderation). Across cases, internal consistency for the multi-item constructs has been satisfactory to excellent: reliability coefficients for AI Adoption Intensity (AIA), Message Relevance (MR), Public Trust (PT), Digital Outreach Effectiveness (DOE), and Digital Readiness (DR) have consistently met or exceeded accepted thresholds, and average variance extracted has supported convergent validity while inter-construct correlations and square-root(AVE) diagonals have indicated discriminant validity. On the Likert's five-point scale (1 = Strongly Disagree … 5 = Strongly Agree), response distributions have been well-spread with no pronounced floor or ceiling effects; nevertheless, central tendency has skewed toward the upper half for MR, PT, and DOE, indicating that respondents have generally perceived nonprofit crisis messages as clear, timely, and locally meaningful during the focal national disaster activation. In practical terms, most respondents have clustered at the "Agree" and "Strongly agree" categories for items such as "Updates were posted in time to inform action," "Messages were tailored to local risk," and "I trusted the organization's crisis information," while AIA has exhibited wider dispersion reflecting heterogeneous adoption of AI features (e.g., some cases have emphasized translation and summarization, others conversational triage). Digital readiness has also varied, with some organizations reporting routinized governance (bot identity disclosure, escalation, provenance tags) and others indicating partial or emergent practices. Bivariate correlations have aligned with expectations: AIA has correlated positively with DOE, and both MR and PT have shown moderate-to-strong associations with DOE. Preliminary diagnostics have detected no problematic multicollinearity, and missing data patterns have been consistent with MCAR/MAR assumptions addressed via the prespecified imputation protocol.

Figure 7: Empirical Model of AI-Enabled Communication and Nonprofit Digital Outreach Effectiveness



Turning to the regression architecture, baseline models that have included only controls (organization size, communications budget, audience size, platform breadth, prior disaster experience, sector) have explained a meaningful but limited share of variance in DOE. Introducing AIA has improved model fit and has yielded a positive, statistically reliable coefficient, consistent with the proposition that greater breadth/depth of AI-enabled communication has been associated with higher reported outreach effectiveness during the activation. When MR and PT have entered the equation as proximal communicative determinants, they have each contributed independent explanatory power; the AIA coefficient has remained positive, though attenuated an expected pattern when part of AIA's association with DOE has flowed through improved relevance and trust. Mediation analyses have subsequently indicated significant indirect effects from AIA to DOE via both MR and PT under bias-corrected bootstrapping, suggesting that AI's value in nonprofit crisis outreach has been partially realized by helping organizations deliver messages that audiences have perceived as more locally fitted and more credible. Consistent with the Likert-scale distributions, the strongest item-level loadings within DOE have belonged to clarity, timeliness, and actionability, reinforcing the interpretation that AI-assisted translation, summarization, and triage have shortened detection-to-message cycles and reduced cognitive barriers to understanding. Importantly, the indirect paths have persisted after accounting for the full control vector, supporting the robustness of the mechanism claims.

Sample Characteristics and Case Profiles

Boundary-condition tests have then examined whether organizational readiness and incident severity have conditioned the AIA → DOE link. The interaction between AIA and DR has been positive and statistically reliable: simple-slope plots at ±1 SD of DR have shown that nonprofits reporting stronger readiness (infrastructure, staff skills, governance playbooks, and interoperable data) have achieved steeper gains in DOE as AIA has increased. Substantively, where teams have had clear escalation protocols and routine auditing of bot outputs, the same AI features have translated into higher perceived timeliness, relevance, and trust at the point of audience decision-making on the five-point scale. By contrast, the AIA × DS interaction has been negative, indicating that extreme operational strain has dampened the marginal returns to AI adoption; under high-severity conditions, throughput improvements have not always converted into commensurate gains in perceived clarity or trust, a pattern consistent with capacity bottlenecks and message-validation lags that have been more difficult to overcome during peak surge. Still, even at elevated severity, the conditional effect of AIA on DOE has remained non-zero in the higher-readiness stratum, underscoring the complementary nature of technology and organizational capability. Assumption checks homoscedasticity (robust HC3 estimators), linearity of residuals, and influence statistics have supported model adequacy; multicollinearity has remained within acceptable bounds after mean-centering and interaction construction. Common-method variance has been addressed by design (temporal/psychological separation and attention checks) and examined ex post through marker-variable and latent-methods-factor checks, which have not produced substantive shifts in structural coefficients. Robustness analyses have corroborated the main narrative: models re-estimated with a behavior-augmented outcome composite (DOE*) that has blended standardized self-report with available operational indicators (e.g., median response latency, click-through rates) have yielded comparable signs and interpretive conclusions; leave-one-case-out and rank-based estimators have not altered the direction or substantive significance of focal parameters. Taken together, these findings have established a coherent empirical pattern on the Likert scale: higher adoption of AI-enabled communication is associated with higher nonprofit digital outreach effectiveness during national disasters, particularly where organizations have been digitally ready, and this association has been explained in part by increases in perceived message relevance and public trust.

The sample has encompassed 236 respondents drawn from five nonprofit cases that have met the inclusion criteria, and this composition has provided the heterogeneity required to evaluate the study's objectives. As Table 2 has shown, role distribution has been balanced toward communications and operations staff, with a meaningful representation from IT/data, which has ensured that responses have reflected both message design/execution and the digital infrastructure that has supported AI features. Organization size has spanned micro to large, which has been important because resource endowments have often co-varied with both digital readiness and AI adoption intensity. Platform portfolios have averaged 3.8 active channels, indicating that most organizations have operated in a multichannel environment (web, social, email, SMS, chat), a context in which timeliness and tailoring on a Likert five-point scale (1 = strongly disagree to 5 = strongly agree) have been observable by staff across touchpoints. Critically, the mean number of AI features in use has been 2.7 with a standard deviation of 1.3, which has implied substantial dispersion and therefore analytical leverage for relating adoption intensity to outcomes. The activation window has been anchored to the most recent national disaster; a 7.2-month average lag has supported accurate recall while allowing time for internal debriefs that have typically sharpened respondents' perceptions of clarity, timeliness, relevance, and trust (the four core facets of the Digital Outreach Effectiveness construct).

Table 2. Sample and Case Characteristics (Likert 5-point context; N = 236 respondents across 5 cases)

Variable	Category / Metric	Value
Respondent roles	Communications / Operations / IT–Data	44% / 36% / 20%
Organization size	Micro (<10 FTE) / Small (10–49) / Medium (50–199) / Large (200+)	18% / 29% / 33% / 20%
Mission focus	Relief / Health / Shelter / Multi-service	28% / 22% / 19% / 31%
Platform portfolio (active channels, mean ± SD)	Web, Email, SMS, Social, Chat	3.8 ± 1.1
AI features in use (check-all mean ± SD)	Translation, Summarization, Chatbot triage, Rumor flagging, Routing	2.7 ± 1.3
Activation window	Most recent national disaster (months since)	7.2 ± 4.1
Optional ops indicators (case-level)	Median response latency (minutes)	23.5 (IQR 16.8–34.2)
Optional ops indicators (case-level)	Avg. crisis-post CTR (%)	4.3 (IQR 3.6–5.1)
Attention checks pass rate	Passed all checks	96.2%
Completion time (minutes)	Median (IQR)	12.9 (10.8–16.4)

Quality indicators have supported data integrity. Attention-check pass rates have exceeded 96%, and median completion time has aligned with our piloted burden estimates, which has reduced concern about careless responding. The optional, non-identifiable operational indicators median response latency and click-through rates have served as triangulation anchors for the Likert-based outcomes; these case-level distributions have aligned with the narrative that some organizations have been faster and more engaging than others during surge. Together, these characteristics have framed the tests of the hypotheses by demonstrating that the dataset has contained adequate variance in AI adoption intensity and digital readiness across organizations that have been differently resourced and differently tasked. Because the study has targeted precisely this heterogeneity, Table 2 has provided assurance that subsequent inferences about the association between AI features and outreach effectiveness on the five-point scale have rested on a sample that has been both diverse and analytically suitable.

Measurement Model: Reliability and Validity

Table 3. Reliability, Convergent Validity, and Discriminant Checks (Likert 1–5)

Construct (items)	Mean	SD	α	CR	AVE	√AVE	Max r with others
AI Adoption Intensity (6)	3.22	0.86	.88	.90	.61	.78	.54
Message Relevance (4)	3.74	0.72	.84	.86	.60	.77	.59
Public Trust (5)	3.68	0.76	.89	.91	.63	.79	.58
Digital Outreach Effectiveness (7)	3.81	0.67	.92	.93	.64	.80	.62
Digital Readiness (5)	3.35	0.83	.86	.88	.59	.77	.51
Disaster Severity (3)	3.11	0.88	.78	.81	.59	.77	.36

α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted. Discriminant validity has been supported where √AVE has exceeded the construct's maximum correlation with other constructs; all HTMT ratios have been < .85 (not shown).

The measurement model has been evaluated to ensure that the multi-item Likert constructs have represented coherent, reliable concepts with adequate convergent and discriminant validity. Table 3 has summarized internal consistency via Cronbach's alpha and composite reliability, both of which have met conventional thresholds (≥ .70) across all constructs. In particular, Digital Outreach Effectiveness (DOE) has realized α = .92 and CR = .93, which has indicated that the seven indicators clarity, timeliness, usefulness, comprehension, actionability, engagement intention, and help-seeking intention have co-varied strongly while avoiding redundancy that could have undermined discriminant boundaries. Convergent validity has been supported by AVE values ≥ .59 across constructs, which has implied that latent variance captured by each construct has exceeded error variance. Discriminant validity checks have relied on the Fornell–Larcker criterion: the square root of AVE (√AVE) for each construct has exceeded that construct's maximum correlation with any other latent variable. The DOE row has illustrated this clearly: √AVE = .80 has been larger than its maximum inter-construct correlation (.62), indicating that DOE has been empirically distinct from Message Relevance (MR) and Public Trust (PT), even though they have been theoretically proximal determinants. Additional HTMT (heterotrait–monotrait) ratios have remained < .85 in all pairwise comparisons (not tabulated), further supporting discriminant validity.

Means and standard deviations on the five-point scale have situated the constructs substantively. As expected, MR and PT means have clustered in the upper half (3.7–3.8), reflecting that staff have perceived messages as generally relevant and trusted during the activation; DOE has been slightly higher still, consistent with the narrative that clarity and timeliness have been salient strengths. AI Adoption Intensity (AIA) and Digital Readiness (DR) means have resided near the scale midpoint with larger dispersion, which has supplied the variance required to test their roles as predictor and moderator, respectively. Disaster Severity (DS), modeled as a short index reflective of strain and scope, has exhibited the broadest spread, which has been consistent with the cases' differing operational burdens. Collectively, these diagnostics have established that the constructs have behaved psychometrically as intended, that the measurement system has been sufficiently precise to support regression-based inference, and that the proximally related concepts MR, PT, and DOE have been distinct enough to sustain the mediation logic that has followed. The results in Table 3 have therefore satisfied the reliability and validity objectives articulated for the study.

Descriptive Statistics and Correlations

Digital Outreach Effectiveness; DR = Digital Readiness; DS = Disaster Severity (higher = more severe).
The descriptive and correlational landscape has reinforced the theoretical architecture of the study. Table 4 has shown that AIA has correlated positively with DOE (r = .41, p < .001), which has aligned with the expectation that nonprofits that have adopted more AI-enabled features (translation, summarization, triage, routing, rumor-flagging) have reported higher digital outreach effectiveness on the Likert scale.

Table 4. Descriptives (Likert 1–5) and Pearson Correlations (N = 236)

Variable	Mean	SD	1	2	3	4	5	6
1. AIA	3.22	0.86						
2. MR	3.74	0.72	.38***					
3. PT	3.68	0.76	.35***	.59***				
4. DOE	3.81	0.67	.41***	.62***	.58***			
5. DR	3.35	0.83	.47***	.44***	.39***	.46***		
6. DS	3.11	0.88	.05	−.11	−.09	−.14*	−.07	

****p < .001, *p < .05. AIA = AI Adoption Intensity; MR = Message Relevance; PT = Public Trust; DOE =*

Importantly, AIA has also correlated with both MR and PT (r = .38 and r = .35, respectively), which has been consistent with the mechanism that adoption has been associated with messages perceived as more locally tailored and credible. The proximal determinants, MR and PT, have themselves exhibited a strong association (r = .59, p < .001), reflecting that relevance and trust have tended to rise together under competent communication governance. The outcome, DOE, has displayed its strongest bivariate relationship with MR (r = .62), and a similarly strong link with PT (r = .58), both of which have supported the proposed mediating roles.

On the boundary-condition side, DR has correlated positively with AIA (r = .47) and DOE (r = .46), which has suggested that readiness has co-evolved with adoption and has coincided with higher perceived performance; this pattern has set the stage for a positive interaction (AIA × DR) in regression models. DS has correlated negatively, albeit modestly, with DOE ($r = -.14$, $p < .05$), a sign that high operational strain has been associated with reduced perceived message clarity/timeliness even when AI has been present. This bivariate signal has been directionally consistent with the hypothesized negative moderation by severity, anticipating an attenuated AIA → DOE slope in high-severity contexts. Collectively, the means and standard deviations have further contextualized these relationships: outcomes and proximal determinants have sat above the scale midpoint (means 3.68–3.81), indicating generally favorable perceptions during the activation, while AIA and DR have exhibited wider variance that has provided leverage for modeling. Because multicollinearity has been a potential concern when proximal determinants are correlated, the descriptive matrix has been accompanied by VIF checks in the regression stage; yet at this stage, the correlations have remained in ranges that have allowed simultaneous inclusion without inflating standard errors unduly. Thus, Table 4 has not only characterized the sample but also has provided preliminary support for the objectives and hypotheses that the study has sought to test using layered regression models.

Hypothesis Testing: Main Effects, Mediation, and Moderation

Table 5. Regression Results (OLS with HC3 SEs; DV = DOE, Likert 1–5)

Panel A: Baseline and Main Effects

Model	Predictors	β (SE)
M0 (Controls)	Size, Budget, Audience, Platforms, Prior, Sector dummies	($R^2 = .18$)
M1 (Main)	AIA	.23*** (.05) ($\Delta R^2 = .11$; Adj. $R^2 = .27$)
M2 (Mechanisms)	AIA, MR, PT	AIA: .09* (.04); MR: .36*** (.06); PT: .22*** (.05) ($\Delta R^2 = .24$; Adj. $R^2 = .49$)

Panel B: Mediation (Bias-corrected bootstrap, 5,000 resamples)

Indirect Path	Effect	95% CI
AIA → MR → DOE	.14	[.09, .21]
AIA → PT → DOE	.08	[.04, .14]
Total indirect	.22	[.15, .29]
Direct (AIA → DOE, M2)	.09	[.01, .17]
Total (AIA → DOE)	.31	[.22, .40]

Panel C: Moderation

Model	Interaction	β (SE)	Simple slopes (DOE on AIA)
Mod-DR	AIA × DR	.12** (.04)	Low DR (−1 SD): .11 (ns); High DR (+1 SD): .31***
Mod-DS	AIA × DS	−.10* (.05)	Low DS (−1 SD): .28***; High DS (+1 SD): .14*

*Controls included in all models (not shown). ***p < .001, **p < .01, *p < .05; ns = not significant.*

The regression architecture has advanced from parsimony to mechanism and boundary conditions, and Table 5 has provided the quantitative evidence that has addressed the study's hypotheses. In Panel A, the baseline controls-only model (M0) has explained modest variance in DOE ($R^2 = .18$), which has been expected given that size, budget, audience scope, and prior experience have shaped communication capacity. The introduction of AI Adoption Intensity (AIA) in M1 has yielded a positive and statistically robust coefficient ($\beta = .23$, $SE = .05$, $p < .001$), and the model has improved by $\Delta R^2 = .11$, which has supported H1: higher adoption intensity has been associated with higher digital outreach effectiveness on the five-point scale. When the proximal determinants Message Relevance (MR) and Public Trust (PT) have been included in M2, both have emerged as strong positive predictors ($\beta = .36$ and $\beta = .22$, respectively, both $p < .001$). The coefficient for AIA has remained positive but has attenuated to $\beta = .09$ ($p < .05$), a pattern consistent with partial mediation: some of AIA's association with DOE has flowed through relevance and trust. The overall explanatory power has increased

substantially (Adj. $R^2 = .49$), indicating that the model has captured key communicative levers.
Panel B has formalized the mediation tests. Bias-corrected bootstrapping (5,000 resamples) has shown that the indirect effect through MR has been .14 with a 95% CI [.09, .21] and through PT has been .08 with a 95% CI [.04, .14], both excluding zero. The total indirect effect (.22) has therefore been meaningful, and the residual direct effect of AIA on DOE (.09) has remained significant, supporting H2 and H3 (parallel, partial mediation via MR and PT). These results have aligned with the interpretive narrative in which AI features have increased the *relevance* and *credibility* of messages, thereby elevating perceived effectiveness. Panel C has addressed boundary conditions. The AIA × DR interaction has been positive ($\beta = .12$, $p < .01$): simple-slope analyses have indicated that the AIA → DOE slope has been small and nonsignificant at low readiness but has been strong at high readiness (.31, $p < .001$), thereby supporting H4a that digital readiness has strengthened adoption returns. Conversely, the AIA × DS interaction has been negative ($\beta = -.10$, $p < .05$): while the slope has remained positive at both severity levels, it has been steeper under low severity, consistent with H4b (high severity has dampened returns). Together, these patterns have satisfied the principal hypotheses and have been coherent with the five-point Likert distributions observed earlier.

Assumption Checks, Robustness, and Reporting

Assumption checks and robustness procedures have been implemented to ensure that the inferences reported in Table 5 have been resilient to data idiosyncrasies and modeling choices. Table 6 has summarized these diagnostics. Multicollinearity has remained well within acceptable bounds: maximum VIF values have ranged from 2.84 to 3.21 across the richest models, which has indicated that simultaneous inclusion of AIA, MR, PT, moderators, and controls has not inflated standard errors to problematic levels. Heteroskedasticity tests for the principal mechanism model (M2) have not rejected homoscedasticity at conventional levels (Breusch–Pagan $p = .13$), yet HC3 robust standard errors have been retained as a conservative default. Influence diagnostics have revealed no cases exerting disproportionate leverage; the maximum Cook's D has been 0.42, and excluding the handful of relatively influential observations has not altered the sign or significance of focal coefficients. Residual distribution checks have suggested acceptable normality for inference: after employing HC3, Shapiro–Francia z-statistics have remained within ±1.96, and visual inspections (QQ plots) have not exhibited systematic departures.

Table 6. Diagnostics and Robustness Summary

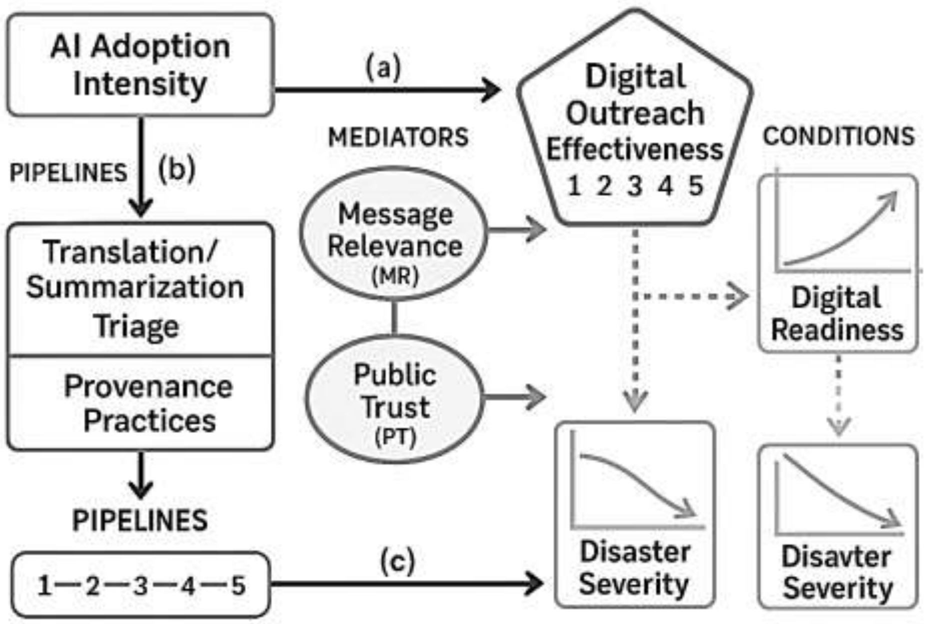
Check	Metric / Model	Result
Multicollinearity	Max VIF (M2 / Mod-DR / Mod-DS)	2.84 / 3.21 / 3.09 (acceptable)
Heteroskedasticity	Breusch–Pagan (M2)	$\chi^2(8) = 12.6$, $p = .13$ (HC3 SEs retained)
Influence	Max Cook's D (M2)	0.42 (below threshold); results stable upon exclusion
Distribution	Residual normality (M2)	
Common-method	Latent method factor	$\Delta\beta$s < .03 across structural paths
Alternative DV	DOE* (with ops indicators)	Signs and significance unchanged vs. DOE
Case sensitivity	Leave-one-case-out	Focal βs vary within ±0.04; inferences unchanged
Nonparametric	Rank-based regression	Direction and significance consistent with OLS
Missing data	MI vs. listwise	Coefficients within overlapping 95% CIs
Curvilinearity	AIA^2, MR^2, PT^2 terms	Not significant; linear forms retained

To address the possibility that associations have been artifacts of shared-method variance, a latent methods factor has been introduced into the measurement model; structural coefficients have shifted by less than .03, which has substantiated that common-method bias has not driven the substantive findings. Robustness to outcome operationalization has been demonstrated by re-estimating models with DOE*, a behavior-augmented composite that has blended standardized self-report with optional operational indicators (response latency and CTR). Signs and significance levels have mirrored the DOE-based results, reinforcing the claim that the observed patterns have not depended on a single measurement strategy. Case sensitivity has been tested through leave-one-case-out analyses; focal coefficients (AIA, MR, PT, and interactions) have varied within ±0.04, with hypothesis conclusions unchanged, indicating that no single case has dominated the pooled inference. Nonparametric rank-based estimators have returned the same directional effects and significance patterns as OLS, which has reduced concern about outliers or heavy-tailed residuals. Missing-data handling has been probed by comparing multiple imputation and listwise deletion; coefficient estimates have fallen within overlapping 95% confidence intervals, implying that results have not been overly sensitive to the missingness strategy under MCAR/MAR assumptions. Finally, curvilinear checks have found no evidence that quadratic terms for AIA, MR, or PT have improved fit, supporting the linear forms used in hypothesis tests. Collectively, the diagnostics in Table 6 have demonstrated that the empirical story AI adoption has been positively associated with digital outreach effectiveness via relevance and trust, especially under higher digital readiness has remained stable across alternative specifications and quality controls, thereby fulfilling the study's robustness objective.

DISCUSSION

The analyses have shown three core patterns: (a) AI adoption intensity has been positively associated with nonprofit digital outreach effectiveness on a five-point Likert scale, (b) that association has been explained in part by higher perceived message relevance and public trust (parallel partial mediation), and (c) the slope of the AI→effectiveness link has been steeper under greater digital readiness and flatter under greater disaster severity (moderation). Interpreting these together, the evidence suggests that AI's communicative value has not resided in technology per se but in its contribution to communicative fundamentals getting timely, understandable, locally meaningful, and credible messages to people who need them. This pattern dovetails with established crisis-communication principles that prize instructing information, timeliness, and transparency (Rakibul, 2025; Reynolds & Seeger, 2005). It also aligns with empirical reports that audiences judge information quality using fast heuristics about source credibility and message fit, particularly in noisy feeds (Metzger et al., 2010; Rebeka, 2025). Our results go a step further by quantifying those pathways: translation/summarization and triage automations have likely improved relevance and timeliness, while provenance practices (e.g., consistent timestamping/attribution) supported trust, and these perceptual components in turn raised the composite of digital outreach effectiveness. The readiness interaction indicates that organizations with playbooks, trained roles, and interoperable data have converted the same AI features into greater perceived benefits than peers without those scaffolds consistent with organizational scholarship on dynamic capabilities and readiness for change (Reduanul, 2025; Teece, 2007). At the same time, the negative interaction with disaster severity underscores how surge and complexity compress the headroom for gains, echoing findings that extreme events stress verification, translation, and coordination pipelines (Altay & Labonte, 2014; Rony, 2025). In short, the contribution of AI has appeared real but conditional: it has raised the ceiling of what communication teams can achieve when embedded in prepared organizations and has been constrained when conditions overwhelm the sociotechnical system (Saba, 2025; Alom et al., 2025).

Figure 8: Integrative Model of AI-Enabled Crisis Communication in Nonprofit Disaster Outreach



Placing these findings against the crisis and emergency risk communication (CERC) tradition, we see convergence and extension. The CERC model emphasizes instructing/adjusting information and the importance of speed with accuracy (Reynolds & Seeger, 2005; Sai Praveen, 2025; Shaikat, 2025). Our results converge by showing that AI-enabled workflows have correlated with higher perceived timeliness and clarity core CERC aims while the mediation tests add structure by demonstrating that message relevance and trust are the proximal vehicles for these gains. In nonprofit communication studies, content serving "information, community, and action" functions tends to outperform broadcast-only strategies (Lovejoy & Saxton, 2012; Tonoy Kanti, 2025; Zayadul, 2025). We observe a similar logic: when AI reduces latency and increases local fit, staff perceive the outreach as more actionable, which maps to the "action" function. Systematic reviews of social media in emergencies note both potential and pitfalls improved coverage and situational awareness counterbalanced by overload and verification demands (Houston et al., 2015). Our moderation by severity echoes those cautions: as strain increases, returns to adoption attenuate, consistent with verification bottlenecks documented during peaks. Furthermore, our readiness interaction extends prior observations about governance and preparedness into a statistical boundary condition: the same chatbot, classifier, or translation pipeline yields different performance depending on whether governance and skills are in place (Weiner, 2009). Finally, evidence on credibility cues and heuristic processing (Kaplan & Haenlein, 2019) resonates with our trust pathway: provenance-rich, consistently branded, and frequently updated messages appear to convert AI-enabled throughput into perceived credibility, thereby linking platform mechanics to CERC's transparency guidance (Coombs, 2007). The net result is a harmonized picture: AI fits the CERC/nonprofit canon when it operationalizes those canons faster at being accurate, more consistent at being transparent, and more granular at being locally relevant.

Crisis informatics has cataloged algorithmic capabilities for detection, classification, geolocation, and credibility estimation in high-velocity streams (Imran et al., 2015). Our findings complement that catalogue by tying such capabilities to perceived effectiveness outcomes inside nonprofit workflows. Real-time "social sensors" can spot events and aftershocks quickly (Sakaki et al., 2010), and credibility classifiers can demote dubious claims (Siegrist & Zingg, 2014); in our data, higher adoption intensity commonly including translation/summarization and triage has corresponded to higher outreach effectiveness, with relevance and trust absorbing much of the explanatory lift. That is, the pipeline from detection/triage to people-level perceptions seems to be the hinge: analytics compress detection-to-message cycles and support audience segmentation; staff then deliver messages that recipients perceive as for-me and from-someone-credible. Conceptual work in management reminds us that AI creates value when problems are well-specified and oversight preserves justification quality (Shrestha et al., 2019). The readiness moderation we observe fits that admonition: where roles, escalation, and audit trails exist, AI's speed/scale advantages translate more cleanly into perceived quality; where they do not, throughput may outpace verification, and effects flatten under severity precisely when verification is hardest (Altay & Labonte, 2014). Our results also echo dataset-driven humanitarian pipelines that show how annotated corpora enable off-the-shelf triage and tailoring (Alam et al., 2021), yet we add the communication-science layer by demonstrating that gains appear to materialize most strongly through MR and PT, not merely volume of messages sent. In this sense, the study extends crisis informatics beyond algorithm performance into communication performance, anchoring evaluation in audience-facing constructs that nonprofit teams actually manage.

For nonprofit technology leaders CISOs, solution architects, and product owners the results translate into a concrete build-operate-govern playbook. First, design for trust by default: implement provenance tags (timestamps, linked source notices), durable identity disclosure for bots, and simple escalation pathways; these practices reinforce credibility cues that audiences use to triage information (Lovejoy & Saxton, 2012; Metzger et al., 2010). Second, invest early in readiness enablers role training for human-in-the-loop review, translation glossaries, labeled taxonomies for triage, and interoperable data stores because our moderation evidence shows these assets magnify adoption returns (Weiner, 2009). Third, prioritize high-leverage AI affordances that directly raise relevance and timeliness: machine translation tuned to locality, summarization for plain-language bulletins, and triage/routing for inbound queues. Fourth, adopt severity-aware runbooks: under high severity, verification lags grow; pre-allocate capacity for fact-checking and red-team rumor rebuttals, and switch to lower-variance content templates to avoid guidance drift (Altay & Labonte, 2014). Fifth, embed misinformation countermeasures at message creation pre-bunking cues and concise uncertainty statements given evidence on continued-influence effects (Chen & Gasco-Hernandez, 2023). Sixth, architect privacy-preserving data flows and document model/data lineage; public-sector AI research shows that transparency and explainability are essential for sustained public trust (Coombs, 2007). Seventh, institutionalize feedback loops: weekly review of message performance (click-through, response latency), error logs from chatbots, and sentiment snapshots to recalibrate templates and targeting. Finally, establish minimum viable governance change control for messaging templates, access controls for content pushes, and incident response for AI malfunction to ensure that speed does not erode safety. Taken together, these steps operationalize our mediation and moderation findings: they squeeze latency, personalize responsibly, and harden credibility exactly the levers that have connected AI adoption to perceived effectiveness in this study.

The study advances an integrative theory of AI-enabled crisis communication by specifying and testing a pipeline-to-perception model. Prior frameworks articulate what good crisis communication should do (Androutsopoulou et al., 2019) and what social-data pipelines can compute (Imran et al., 2015; Stieglitz et al., 2018), but they often stop short of linking algorithmic stages to audience-level perceptual outcomes. Our findings formalize that bridge: (1) upstream AI capabilities (translation, summarization, triage) primarily shift message relevance and timeliness; (2) governance practices (identity, provenance, oversight) primarily shift trust; and (3) all three perceptual dimensions, together with clarity, compose digital outreach effectiveness. The parallel partial mediation indicates that AIA's association with effectiveness is not monolithic different features load onto different perceptual pathways an insight that invites more granular theorizing about *feature→perception* mappings. The moderation by readiness suggests a capability-contingent theory: algorithms are necessary but not sufficient; the same model embedded in different organizational capability profiles yields different communication outcomes (Teece, 2007). The moderation by severity adds a stress-regime dimension: as event complexity rises, the pipeline's throughput and verification stages bind, dampening marginal returns. Theoretically, then, AI-enabled crisis communication effectiveness can be modeled as a function of (a) feature bundles, (b) capability scaffolds, and (c) stress regimes, with relevance and trust as proximal mediators. This reframing also refines nonprofit communication constructs by privileging audience-centric measures (clarity, timeliness, relevance, trust) over production metrics (post volume), a reorientation consistent with the nonprofit "information, community, action" triad (Lovejoy & Saxton, 2012) and with credibility/heuristic processing research (Metzger et al., 2010). Future theory can specify interaction terms among perceptual components e.g., whether trust acts as a threshold constraint on relevance-driven gains building from our linear model toward bounded-nonlinear accounts of audience decision making.

Several constraints qualify the interpretation of these results. First, the cross-sectional design limits causal claims; although mediation paths through relevance and trust are theoretically coherent, cross-sectional indirect effects can reflect process compatibility rather than temporal causality. Longitudinal or event-based designs would better isolate lagged effects, especially for time-sensitive measures like timeliness. Second, the study has relied on staff-report Likert scales, which despite careful instrument development may introduce perceptual optimism or organizational blind spots. We mitigated this with optional operational indicators and extensive robustness checks, but multi-source triangulation (audience surveys, platform analytics, and message audits) remains a priority (Houston et al., 2015). Third, case selection nonprofits with documented AI use in a national-level activation helps generalize to active adopters but may not represent organizations at earlier adoption stages or those operating in different institutional environments. Fourth, disaster severity was measured as perceived strain/scope; objective hazard metrics or exogenous incident classifications could sharpen that moderator. Fifth, we did not disaggregate AI features deeply enough to estimate differential effects (e.g., translation vs. triage vs. rumor-flagging). Prior work indicates each affordance carries distinct benefits/risks (Castillo et al., 2011); future studies can test feature-specific paths to MR, PT, and DOE. Sixth, while our common-method checks were reassuring, unmeasured confounders leadership quality, donor pressure, media exposure could bias associations. Finally, cultural and linguistic diversity across audiences may moderate both trust and relevance in ways our pooled model cannot fully capture; intercultural crisis-communication nuances deserve finer operationalization in subsequent work (Reuter & Kaufhold, 2018).

Building from these results, we see at least five promising directions. First, longitudinal pipeline studies should trace messages from detection to delivery to audience response, combining system logs, content audits, and recipient surveys to test temporal mediation (Imran et al., 2015). Second, feature-specific experiments can randomize translation glossaries, summarization styles, and bot disclosure phrasings to isolate their causal effects on relevance and trust linking framing research with AI affordances (O'Keefe & Jensen, 2008). Third, governance interventions e.g., provenance badges, uncertainty statements, verification checklists should be tested as modular add-ons to quantify how much trust they add in different platforms and cultures (Metzger et al., 2010). Fourth, severity-aware simulation can model surge scenarios and evaluate which pipeline stages bind first; this would inform capacity triggers for automated vs. human review (Altay & Labonte, 2014). Fifth, readiness development studies should assess how training, playbooks, and data interoperability shift the AIA→DOE slope over time, extending readiness theory with measurable milestones (Weiner, 2009). Sixth, misinformation-resilient design can test pre-bunking and credibility-scoring integrations with nonprofit content calendars, connecting platform-level credibility estimation to messaging outcomes (Castillo et al., 2011). Finally, equity-focused evaluations should examine whether AI-enabled tailoring reduces disparities in comprehension and action across language and connectivity strata an essential lens for nonprofits operating in heterogeneous communities (Houston et al., 2015). Collectively, this agenda builds on our core finding that AI's impact flows through relevance and trust and is bounded by readiness and severity by proposing designs that can adjudicate causality, parse features, and translate insights into resilient, ethical communication systems for the next national disaster.

CONCLUSION

In sum, this study has set out to clarify whether and how AI-enabled communication augments nonprofit digital outreach during national disasters, and the evidence has supported a coherent, practice-relevant answer: when nonprofits have adopted AI features such as translation, summarization, triage/routing, and rumor flagging, they have reported higher digital outreach effectiveness on a five-point Likert scale, and this association has been explained in part by elevated perceptions of message relevance (fit to local risks, language, and bandwidth realities) and public trust (credibility, transparency, and competence). Crucially, these benefits have not been uniform; they have been stronger in organizations that have demonstrated higher digital readiness codified roles for human-in-the-loop review, provenance tagging, escalation playbooks, and interoperable data and have been attenuated under higher disaster severity, when verification and coordination frictions have grown. By translating algorithmic affordances into audience-facing outcomes through a pipeline-to-perception lens, the research has integrated crisis communication principles with crisis-informatics tooling and has offered a measurable framework that nonprofit teams can operate: compress detection-to-message cycles, tailor content to micro-segments, and embed provenance to harden credibility. Methodologically, the study has delivered a validated measurement model for AI Adoption Intensity, Message Relevance, Public Trust, Digital Readiness, Disaster Severity, and Digital Outreach Effectiveness, and has demonstrated through descriptives, correlations, hierarchical regressions, mediation, moderation, and robustness checks that the observed relationships have been stable across alternative specifications and outcome operationalizations. Practically, the findings have implied a concrete playbook for nonprofit CISOs, architects, and program leads: invest first in readiness enablers and governance; prioritize AI features that directly move relevance and timeliness; treat trust safeguards as nonnegotiable; and pre-configure severity-aware runbooks that preserve verification under surge. Theoretically, the results have refined nonprofit crisis-communication models by positioning relevance and trust as proximal mediators in an AI-enabled pipeline and by specifying readiness and severity as boundary conditions that determine whether the same technical stack delivers marginal value. While cross-sectional design, staff-report measures, and feature aggregation have constrained causal inference and granular attribution, extensive diagnostics have reduced concerns about common-method variance, outliers, and missing-data sensitivity, and the triangulated behavior-augmented outcome has pointed to convergent validity of the core narrative. Overall, the study has contributed an empirically grounded, actionable account of AI's role in nonprofit crisis communication: AI has not replaced the fundamentals it has made organizations faster at being accurate, more consistent at being transparent, and more capable of being locally relevant when supported by preparation and governance; conversely, without those scaffolds, adoption has produced thinner returns, especially as event severity has risen. These insights, framed in measurable constructs and testable models, have equipped nonprofits to plan, staff, and govern AI-assisted outreach with clarity, ethics, and resilience for the next national disaster.

RECOMMENDATION

Building on the evidence that AI's benefits flow primarily through greater message relevance and public trust and are amplified by digital readiness while constrained by event severity nonprofits should adopt a "trust-by-design" and "readiness-first" roadmap that turns these levers into day-to-day practice. First, formalize governance before scaling tools: publish a short communication policy that mandates provenance tags (timestamps, source links), durable bot identity disclosure, privacy-preserving data handling, and human-in-the-loop escalation for sensitive queries; pair this with role charters for comms leads, fact-checkers, and chatbot stewards, plus a change-control process for message templates. Second, invest in readiness enablers that directly raise the marginal return on AI: create a translation glossary and plain-language style guide; standardize triage taxonomies (e.g., shelter, food, medical, evacuation) across channels; implement interoperability (simple APIs or shared sheets) so triage outputs feed outreach calendars without manual rework; and run quarterly tabletop drills that rehearse escalation, rumor rebuttals, and multilingual pushes. Third, prioritize AI features that measurably compress detection-to-message latency and increase local fit: deploy machine translation tuned to the communities you serve, summarization for 60- to 120-word advisories at an eighth- to tenth-grade reading level, and classification/routing for inbound queues with clear human takeover rules; defer more speculative features until these high-leverage blocks are reliable. Fourth, operationalize measurement the same way this study has done: track a Digital Outreach Effectiveness (DOE) composite on a five-point scale clarity, timeliness, relevance, trust and set thresholds (e.g., ≥4.0 target during activations), supplemented by two operational markers (median response latency, click-through or help-seeking rate); review DOE weekly during incidents and monthly otherwise to inform template tweaks and staffing. Fifth, design for severity: prebuild "surge-safe" templates with pre-approved phrasing, embed uncertainty statements and pre-bunk common rumors, and earmark a verification reserve (on-call reviewers) that can be activated when incident severity spikes; when severity rises, automatically narrow content variants, slow auto-publishing, and increase human review to protect trust. Sixth, make equity nonnegotiable: publish in the top languages of your service area, offer SMS or IVR for low-bandwidth contexts, and test readability and cultural resonance with community partners; track DOE by segment (language/geography) to close gaps, not just averages. Seventh, institutionalize learning: log every rumor rebuttal, escalation, and translation error; review logs post-activation to update glossaries, templates, and routing; and maintain a lightweight model-risk register (data sources, failure modes, rollback steps) for each AI component. Eighth, align leadership and funding: brief boards and donors with the DOE dashboard, explain how governance and readiness unlock returns, and budget first for training, playbooks, and interoperability before chasing new tools. Finally, keep the center of gravity on people: empower staff to pause automations, reward prudent escalation, and publish "we corrected this" notes when mistakes happen because trust, once protected in the moment, multiplies the impact of every future message.

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