Journal of Economics, Finance and Management Studies

ISSN (print): 2644-0490, ISSN (online): 2644-0504

Volume 08 Issue 10 October 2025

Article DOI: 10.47191/jefms/v8-i10-02, Impact Factor: 8.317

Page No: 6582- 6595

Bridging Technology and Readiness: AI, IoT, and the Effectiveness of Disaster Prevention in Climate-Vulnerable Regions

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ABSTRACT: In the context of intensifying climate change, this study explores how artificial intelligence (AI)–driven flood prediction accuracy and Internet of Things (IoT)–based environmental monitoring coverage contribute to disaster prevention effectiveness, with community readiness for technology adoption as a moderating factor. Grounded in Socio-Technical Systems (STS) Theory and the Technology Acceptance Model (TAM)/Unified Theory of Acceptance and Use of Technology (UTAUT), the study adopts a quantitative design with 385 valid responses from Vietnam, Singapore, and Malaysia, representing engineers, ICT managers, disaster officials, and community stakeholders. A structured 5-point Likert scale questionnaire was developed, to evaluate perceptions of predictive accuracy, monitoring coverage, disaster prevention effectiveness, and community readiness. Data analysis was conducted using SPSS, including reliability assessment (Cronbach's alpha), exploratory factor analysis (EFA), linear regression, and moderation analysis with the PROCESS Macro to test the hypothesized relationships. Findings confirm that AI predictive accuracy enhances prevention not merely through numerical precision but by providing timely, actionable warnings. Likewise, IoT monitoring improves situational awareness, yet its value depends on strategic deployment, interoperability, and usability. Importantly, community readiness encompassing trust, literacy, affordability, and willingness to adopt emerges as the decisive factor that enables technological infrastructures to translate into protective action. The study advances theory by integrating socio-technical and adoption perspectives and offers practical insights, urging policymakers to invest not only in infrastructures but also in readiness-building, participatory engagement, and trust-enhancing initiatives.

KEYWORDS: Disaster prevention effectiveness; AI-driven flood prediction; IoT environmental monitoring; Community readiness; Socio-Technical Systems Theory; TAM; UTAUT; Climate change resilience.

I. INTRODUCTION

In the context of intensifying climate change and the increasing frequency of extreme weather events, disaster prevention has become a critical focus for both policymakers and researchers (Wen et al., 2023). Technological innovation, particularly the integration of artificial intelligence (AI) and the Internet of Things (IoT), offers transformative potential for enhancing disaster prediction, monitoring, and preparedness (Ali et al., 2022; Narayana et al., 2024). AI-driven flood prediction systems provide advanced forecasting accuracy, while IoT-enabled environmental monitoring networks expand real-time situational awareness across hazard-prone regions. Together, these technologies promise to shift disaster management from reactive response to proactive prevention, thereby reducing risks and vulnerabilities.

Despite these advancements, disaster prevention effectiveness cannot be guaranteed by technological innovation alone. Research highlights that technological precision and monitoring coverage are often undermined when communities lack the readiness, trust, and institutional support to act upon the generated data (Sinha et al., 2019; Brar et al., 2022). Socio-Technical Systems (STS) Theory emphasizes the need for alignment between technical systems and social actors, while the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) explain the micro-level mechanisms that drive adoption and behavioral change (Venkatesh et al., 2003; Tseng and Stojadinović, 2024). However, existing scholarship frequently evaluates either technical performance or social adoption in isolation, overlooking how community readiness moderates the translation of AI and IoT innovations into effective disaster prevention outcomes. This creates a significant research gap in understanding the integrative pathways through which socio-technical systems shape resilience.

This study addresses this gap by examining how AI-driven flood prediction accuracy and IoT-based environmental monitoring coverage influence disaster prevention effectiveness, with a particular focus on the moderating role of community readiness for technology adoption. By situating these variables within an integrated STS–TAM/UTAUT framework, the research contributes to a holistic understanding of disaster technology adoption and its role in advancing resilience against climate-induced hazards. To guide this investigation, the study addresses the following research questions:

1. To what extent does AI-driven flood prediction accuracy enhance disaster prevention effectiveness?
2. How does IoT-based environmental monitoring coverage contribute to disaster prevention outcomes?
3. In what ways does community readiness moderate the relationship between AI-driven flood prediction accuracy and disaster prevention effectiveness?

II. LITERATURE REVIEW

2.1. Disaster Prevention Effectiveness

Disaster prevention effectiveness refers to the extent to which strategies, technologies, and policies successfully reduce or eliminate the risks and impacts of natural hazards before they occur. Unlike disaster response, which focuses on post-event recovery, prevention emphasizes proactive measures that minimize exposure and vulnerability through anticipatory action (Math et al., 2015; Gao et al., 2025; Keim, 2018). It is conceptually distinct from mitigation, which reduces the severity of consequences once a hazard has already unfolded. Prevention aims to avoid or neutralize disaster impacts altogether, though this distinction is often debated in disaster studies (Math et al., 2015). Scholars note that while prevention is aspirational, mitigation is often regarded as more practically achievable. Nevertheless, prevention effectiveness remains a vital evaluative lens in an era where climate change intensifies hazard frequency and complexity, requiring strategies that move beyond reactive management (Gailmard and Patty, 2018; Wen et al., 2023).

The term “effectiveness” itself is contested, as its meaning varies across institutional and community perspectives. For governments, effectiveness is frequently measured in terms of economic savings, infrastructure protection, and continuity of critical services. By contrast, communities often judge prevention outcomes by the protection of lives, livelihoods, and cultural assets, as well as reduced displacement during hazard events (Mechler, 2016). These divergent perspectives expand effectiveness metrics beyond immediate indicators such as reduced mortality or minimized property loss, to include broader measures such as improved early warning lead times, enhanced adaptive capacity, and strengthened trust in disaster governance systems. Such multiplicity underscores the need to clarify evaluative criteria, as inconsistent definitions limit the comparability of research findings and hinder alignment across policy frameworks.

A critical gap in existing research lies in the limited examination of end-to-end socio-technical pathways that shape prevention outcomes. Much of the current scholarship evaluates isolated components for example, the predictive accuracy of artificial intelligence (AI) models or the reliability of IoT-enabled sensors without considering how these technologies interact within the broader disaster prevention chain (Yu and He, 2022). True prevention effectiveness requires successful integration across multiple stages: hazard detection, prediction and modeling, alert dissemination, community interpretation, and protective response (Haque et al., 2024). Breakdowns at any link whether due to technical failures, inadequate communication, or social non-adoption undermine overall effectiveness. This highlights the need for integrative approaches that move beyond narrow technical assessments to examine how socio-technical systems as a whole translate innovations into tangible resilience gains. Without this full-pipeline perspective, it remains unclear whether advancements in AI and IoT meaningfully enhance disaster prevention or merely strengthen isolated technical capabilities.

2.2. Theoretical framework

The present study is grounded in an integrative theoretical framework that combines Socio-Technical Systems (STS) Theory and the Technology Acceptance Model (TAM)/Unified Theory of Acceptance and Use of Technology (UTAUT). Together, these theories capture both the technical dimension (AI-driven prediction and IoT-based monitoring) and the social dimension (community readiness), thereby enabling a holistic understanding of how disaster prevention effectiveness emerges.

2.2.1. Socio-Technical Systems (STS) Theory

Socio-Technical Systems (STS) Theory posits that organizational performance results from the joint optimization of technical subsystems (tools, technologies, and processes) and social subsystems (people, communities, and institutions). According to Trist and Bamforth (1951), systems only achieve their full potential when both subsystems are aligned rather than optimized in isolation. In disaster management, this perspective highlights that the technologies such as AI-based prediction models and IoT monitoring infrastructures will not automatically deliver effectiveness without parallel social preparedness (Tseng and Stojadinović, 2024; Walker et al, 2007).

Disaster prevention effectiveness can be conceptualized as an emergent system-level outcome that arises when technical solutions (prediction accuracy, monitoring coverage) are integrated with social acceptance and readiness. From an STS perspective, effectiveness is not reducible to technical capacity alone but depends on whether communities understand and respond to technological outputs (Chilvers, Pallett and Hargreaves, 2018). STS has been validated across domains where technology–human interactions are critical. For instance, Kleiner et al. (2011) demonstrated its explanatory power in complex safety systems, arguing that technical improvements without human adaptation rarely lead to better outcomes. Similarly, Tseng and Stojadinović (2024) showed that socio-technical integration increases system resilience during crises, frameworks like CI-STR demonstrate that resilience is shaped by the dynamic interplay between social and technical factors, with human capabilities serving as the interface that links individuals' social characteristics to community resources and technical infrastructure. This integration creates feedback loops where changes in one domain influence the other, enabling communities to adapt and recover more effectively after disasters. These findings reinforce that disaster prevention technologies are effective only when embedded in socially attuned systems.

The relevance of STS becomes more evident when considering the interplay among all variables in this study. Within the technical subsystem, AI-driven predictive accuracy provides a crucial informational resource, and IoT-enabled environmental monitoring expands the scope of data collection across geographies. AI models, such as artificial neural networks and hybrid architectures, have demonstrated high predictive accuracy in applications like water quality assessment, pollution detection, and even earthquake prediction, with some models achieving over 95% accuracy and significant reductions in error rates compared to traditional methods (Zhang et al., 2021). However, STS reminds us that disaster prevention technologies reach their full potential only when embedded in socially attuned systems that foster understanding, preparedness, and coordinated action (Velazquez et al., 2020; Marchezini et al., 2018). For instance, a flood prediction model that achieves high accuracy may still be disregarded if local communities lack the literacy to interpret risk categories, or if decision-makers fail to institutionalize the model into emergency protocols (Munawar, Hammad and Waller, 2022; Mosavi, Öztürk and Chau, 2018). Similarly, broad monitoring coverage may only generate resilience when local responders have clear processes for integrating sensor outputs into coordinated action. In this way, the moderator variable community readiness for technology adoption becomes not simply an external factor but an essential component of the socio-technical balance. It captures whether social actors possess the trust, interpretive capacity, and organizational routines necessary to convert raw technical outputs into collective preventive action. Without this synchronization, the system risks becoming technologically sophisticated yet socially inert, a condition STS explicitly cautions against.

Although STS offers a robust lens to understand the joint optimization of social and technical subsystems, it remains limited in its explanatory precision when applied to disaster technology adoption. One key issue is its level of abstraction: STS emphasizes "alignment" between subsystems but provides little guidance on *how* this alignment is achieved in practice. For instance, while the theory would predict that community readiness must complement AI-driven prediction and IoT monitoring, it does not specify the cognitive or behavioral mechanisms through which individuals decide to trust or reject such systems. Furthermore, STS tends to assume a relatively symmetrical relationship between social and technical domains, yet in real-world disaster contexts, power imbalances, policy constraints, and socio-economic inequalities often privilege one subsystem over the other. This means that even when technical systems are well designed, marginalized communities may lack the institutional capacity or political voice to align effectively, leaving the STS framework insufficient to capture structural inequities. Thus, while STS highlights the importance of integration, it requires supplementation by adoption models that account for the micro-level decision processes and socio-political constraints shaping real outcomes.

2.2.2. Technology Acceptance Model (TAM) / Unified Theory of Acceptance and Use of Technology (UTAUT)

The Technology Acceptance Model (TAM) developed by Davis (1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh et al. (2003) explain why individuals and groups adopt or resist new technologies. These models emphasize perceptions of usefulness, ease of use, facilitating conditions, and trust as key determinants of technology acceptance. UTAUT extends TAM by incorporating social influence and behavioral intention, which are particularly relevant in community-level technology adoption.

Whereas STS provides a macro-level view of system integration, TAM and UTAUT illuminate the micro-mechanisms that link the technical and social elements across variables. The accuracy of AI-driven predictions directly shapes perceptions of usefulness: the more reliable the forecasts, the more likely communities are to regard them as worth adopting (Kelly, Kaye and Oviedo-Trespalacios, 2022). At the same time, IoT-based monitoring influences perceptions of facilitating conditions by ensuring that alerts are localized, frequent, and easily accessible, which in turn reduces perceived barriers to adoption. Crucially, these perceptions feed into the moderator variable community readiness since readiness itself is an aggregate outcome of perceived ease of use, trust, and social influence (Sneesl et al., 2022). If communities believe that prediction outputs are both accurate and actionable, and if monitoring systems are seen as compatible with existing practices, willingness to adopt rises sharply. This psychological acceptance is what ultimately converts technical infrastructures into measurable disaster prevention effectiveness. Thus, TAM/UTAUT clarify why the same technological deployment yields uneven results across different regions: effectiveness depends less on the absolute level of accuracy or coverage, and more on how users interpret, trust, and embed these features into collective routines.

From the perspective of TAM and UTAUT, the explanatory power of the framework goes beyond community readiness to encompass how technical features shape perceptions and behavioral responses. The perceived usefulness of accurate predictions or the accessibility of widespread monitoring coverage directly affects whether individuals and communities accept or dismiss these tools. Importantly, disaster prevention effectiveness emerges not merely from the availability of technological infrastructures but from their acceptance, integration, and habitual use (Sinha et al., 2019). Thus, adoption models highlight the psychological and social mechanisms that translate technical precision into trusted systems, clarifying why similar technologies succeed in some contexts while failing to deliver in others.

In contrast, TAM and UTAUT provide sharper tools for explaining adoption at the individual and community level, but they risk oversimplification by reducing complex socio-technical processes to perceptions such as usefulness, ease of use, and trust. These models are highly effective in predicting initial adoption behavior, yet disaster management requires more than adoption; it requires sustained, collective, and context-sensitive use under conditions of uncertainty and stress. TAM/UTAUT are less equipped to explain how structural factors such as government regulation, cultural norms of risk perception, or unequal access to infrastructure shape readiness and effectiveness beyond individual attitudes (Blut et al., 2022). Moreover, these models assume rational decision-making guided by perceptions, but disaster situations often involve emotional responses, misinformation, and collective dynamics that fall outside the rational-actor paradigm (Lee, Ramasamy, and Subbarao, 2025). As such, TAM/UTAUT may overstate the explanatory power of psychological variables while underestimating the systemic and institutional dimensions of adoption (Blut et al., 2024). This limitation reinforces the need to integrate them with a systems-level theory such as STS, ensuring that adoption is situated not just in individual cognition but in broader socio-technical and political contexts.

2.3. Determinants of Disaster Prevention Effectiveness

2.3.1. AI-Driven Flood Prediction Accuracy

AI-driven flood prediction accuracy refers to the ability of artificial intelligence models to forecast flood events in terms of timing, location, and severity with measurable reliability. Using machine learning and deep learning approaches, these models integrate hydrological, meteorological, and geospatial data to detect patterns that traditional physical models often cannot capture (Ali et al., 2022). Techniques such as neural networks, random forests, and hybrid ensemble methods are increasingly employed to represent nonlinear environmental interactions across multiple scales. Their predictive performance is typically assessed using statistical metrics such as Root Mean Square Error (RMSE), precision, recall, and Area Under the Curve (AUC), which indicate how closely forecasts align with observed outcomes (Islam et al., 2020). These indicators establish the technical validity of AI systems, providing an important baseline for assessing model quality. Yet, focusing solely on these benchmark risks reducing the meaning of “accuracy” to a narrow set of statistical outcomes divorced from practical disaster prevention needs. While AI models often demonstrate strong numerical performance, the notion of “accuracy” remains contested because it carries different implications for researchers, policymakers, and communities (Fang et al., 2020). From a technical perspective, accuracy is defined by minimizing error margins and maximizing statistical fit. However, for end users, operational accuracy the ability of forecasts to provide sufficient lead time for protective actions can be far more valuable than perfect numerical predictions delivered too late. A forecast that predicts floodwater levels with minimal RMSE but issues warnings hours after communities have already been affected offers little preventive utility (Sanders et al., 2022). Conversely, a model with less statistical precision that provides early, actionable warnings can save more lives and property. This tension reveals a gap in existing research, which overwhelmingly privileges technical accuracy while neglecting how predictions function within real-world decision-making contexts (Nearing et al., 2024). Accuracy should therefore be reframed as a multidimensional construct that bridges technical precision with operational usability.

Understanding AI-driven flood prediction accuracy in both technical and operational terms is essential for advancing disaster prevention effectiveness. Accurate predictions, when aligned with lead time requirements, enable timely evacuation planning, efficient allocation of emergency resources, and the safeguarding of critical infrastructure (Nearing et al., 2024; Adikari et al., 2021). However, without mechanisms that translate technical accuracy into actionable community alerts and institutional responses, the practical contribution of AI systems remains limited. This underscores the need to situate AI flood prediction within broader socio-technical pathways, where model outputs are linked to communication systems, governance readiness, and community adoption. Future research must therefore move beyond isolated statistical validation to evaluate whether AI prediction accuracy translates into effective preventive outcomes. Only by integrating accuracy into the full chain of disaster risk reduction can technological progress meaningfully reduce vulnerability and enhance resilience.

Building on theoretical insights and empirical evidence, the study proposes the first hypothesis outlined below:

H1: AI-Driven flood prediction accuracy positively impacts disaster prevention effectiveness.

2.3.2. IoT-Based Environmental Monitoring Coverage

IoT-based environmental monitoring coverage refers to the extent and density of interconnected sensor networks that continuously collect, transmit, and analyze environmental data for disaster prevention purposes. These systems leverage the Internet of Things (IoT) to integrate diverse devices such as rainfall gauges, river-level sensors, soil moisture probes, and air quality monitors into unified platforms capable of generating real-time information flows (Narayana et al., 2024). By expanding spatial coverage across hazard-prone areas and broadening the range of monitored variables, IoT systems strengthen early warning capacity and situational awareness. Conventional measures of coverage typically focus on sensor density and geographic distribution, reflecting the technical infrastructure required for reliable monitoring. These quantitative indicators establish a baseline for evaluating system reach and functionality, but they capture only one dimension of what makes IoT monitoring effective for disaster prevention (Heimann et al., 2021; Okafor, Alghorani and Delaney, 2020).

Although sensor deployment density is often used as the primary measure of IoT coverage, the concept remains contested, since effective coverage involves more than the raw number of devices (Fathy, Barnaghi and Tafazolli, 2018). From technical approaches to enhance coverage include leveraging geo-context information to control data distribution, ensuring that only relevant and location-specific data are collected and disseminated, which increases system efficiency and relevance (Hasenburg and Bermbach, 2020). For decision-makers, “coverage” is meaningful only when information reaches the right institutions in usable formats and in time to inform protective action. A sensor-rich network that generates massive datasets but fails to deliver timely, interpretable information to authorities may be technically expansive but operationally ineffective (Shah et al., 2019). Conversely, a smaller, strategically placed network with high reliability and real-time communication may provide greater disaster prevention benefits. This divergence reveals a gap in the literature, which often privileges quantitative metrics of coverage while overlooking how these networks function within socio-technical systems (Yabe et al., 2022).

Understanding IoT-based monitoring coverage as both a quantitative and qualitative construct has critical implications for disaster prevention effectiveness. Comprehensive and reliable coverage enhances early warning systems, improves hazard detection, and provides decision-makers with the situational awareness needed for timely interventions such as evacuations and resource allocation (Ray, Mukherjee and Shu, 2017). However, without addressing issues of representativeness, accessibility, and exposure-weighted placement, expanded sensor networks risk producing large volumes of data without translating into actionable insights. This underscores the importance of redefining coverage in terms of *effective monitoring*, where system reliability, interoperability, and data usability are given equal weight alongside sensor density (Ejaz et al., 2019; Narayana et al., 2024). Future research must therefore move beyond counting devices toward integrative assessments that evaluate how IoT coverage supports real-world disaster prevention outcomes. By embedding IoT monitoring within broader socio-technical frameworks, scholars and practitioners can better determine whether increased coverage leads to tangible resilience gains.

Grounded in both theory and empirical findings, the study advances the following second hypothesis:

H2: IoT-based environmental monitoring coverage positively impacts disaster prevention effectiveness.

2.3.3. Community Readiness for Technology Adoption

Community readiness for technology adoption refers to the willingness, capacity, and preparedness of local communities to accept, integrate, and act upon technological tools such as IoT-based monitoring systems and AI-driven prediction models. Drawing on frameworks such as the Technology Acceptance Model (TAM) and the Diffusion of Innovations theory (Basarir-Ozel et al., 2023), readiness depends on factors like perceived usefulness, ease of use, trust in technology, and institutional support. In the disaster prevention context, readiness extends beyond simple access to digital infrastructure to include technological literacy, affordability, and social acceptance of automated decision-support systems (Brar et al., 2022). A high level of community readiness ensures that warnings generated by IoT systems are not only received but also understood and acted upon, thereby translating technical coverage into protective action.

The concept of “readiness” remains contested in both academic and practical debates, as it does not carry a single agreed-upon definition. One perspective interprets readiness in narrow, technical terms, focusing on infrastructural capacity such as internet connectivity, device availability, and system interoperability, which are often treated as sufficient indicators of whether a community can adopt technological solutions (Blut and Wang, 2019). From this angle, readiness is equated with the physical presence of digital tools. In contrast, disaster management research increasingly emphasizes that readiness extends beyond infrastructure to encompass socio-cultural and psychological dimensions, including trust in institutions, perceived legitimacy of technology, and willingness to act upon data-driven forecasts (Blut and Wang, 2019; Son and Han, 2011). Some studies suggest that even communities with limited digital infrastructure can still benefit from disaster technologies if they demonstrate high levels of trust, collective preparedness, and social acceptance of technological inputs (Peng et al., 2020; Rayamajhee and Bohara, 2020). The coexistence of these two perspectives illustrates that readiness is not reducible to a single dimension. Instead, it is a multi-layered construct that combines both material access and the behavioral and social conditions necessary to operationalize technological tools (Blut and Wang, 2019). Clarifying this dual nature is essential, as it shapes how community readiness is positioned within disaster prevention research whether as a matter of infrastructure provision or as a broader question of social willingness and institutional trust.

Community readiness critically moderates the relationship between IoT-based environmental monitoring coverage and disaster prevention effectiveness. While broader sensor networks expand the potential for situational awareness, the actual preventive impact depends on whether communities are prepared and willing to act on the data (Ryan et al., 2020). Low readiness can weaken or nullify the benefits of IoT systems: dense networks may generate accurate, real-time data, but without trust, digital literacy, or economic capacity, warnings may go unheeded. Conversely, high readiness amplifies the effectiveness of IoT coverage by ensuring rapid interpretation, collective mobilization, and protective behavior (Sinha et al., 2019). Despite the relevance of this dynamic, limited empirical research has examined readiness thresholds in disaster contexts, leaving unclear whether factors like trust, affordability, and cultural acceptance systematically enhance or constrain IoT's preventive value. Addressing this gap is central to understanding how technological infrastructure interacts with human and social systems, and highlights why community readiness should be positioned as a moderating variable in disaster technology adoption research.

Drawing from the theoretical and empirical foundations, the study develops the third hypothesis presented below:

H3: Community readiness for technology adoption positively moderates the impact of IoT-based environmental monitoring coverage on disaster prevention effectiveness.

Built on established theoretical foundations, this study enhances its academic value by presenting the following conceptual framework:

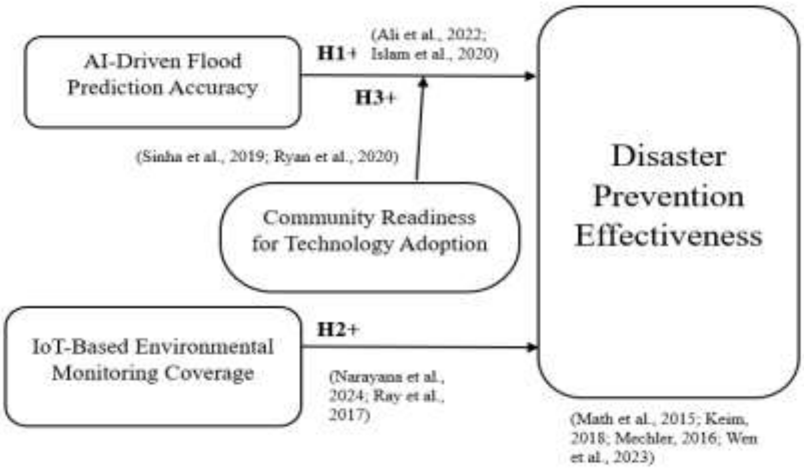

Figure 1. The Paper's Conceptual Framework. ***Source: (The authors, 2025)***

III. METHODOLOGY

This study adopts a quantitative research design to investigate the relationship between AI-driven flood prediction accuracy, IoT-based environmental monitoring coverage, and disaster prevention effectiveness, with community readiness for technology adoption as a moderating factor. A purposive stratified sampling strategy was employed to ensure representation from diverse professional, institutional, and community groups directly involved in the development, deployment, and use of disaster prevention technologies.

Participants were drawn from three countries Vietnam, Singapore, and Malaysia selected for their high exposure to climate-induced hazards, rapid adoption of AI and IoT innovations, and differing levels of community readiness in disaster governance. The sample was stratified into four stakeholder groups: (1) system engineers and data scientists engaged in developing AI-based disaster prediction algorithms; (2) ICT and infrastructure managers overseeing IoT-enabled monitoring systems; (3) disaster management practitioners, emergency response officials, and policy makers responsible for integrating technological outputs into preventive action; and (4) community representatives and academic researchers focusing on disaster resilience, technology adoption, and socio-technical governance. Eligibility criteria required participants to have at least one year of direct experience in disaster risk management, AI/IoT deployment, or community-based resilience programs, as well as familiarity with predictive modeling, environmental monitoring, or disaster prevention strategies. This ensured that responses reflected both technical expertise and practical engagement with disaster technologies.

Data was collected through an online structured questionnaire using a 5-point Likert scale (1 = “Strongly disagree” to 5 = “Strongly agree”). The instrument was designed to measure four constructs: (1) AI-driven prediction accuracy, (2) IoT-based monitoring coverage, (3) perceived disaster prevention effectiveness, and (4) community readiness for technology adoption. The survey was distributed via professional networks, regional ICT and disaster management associations, research institutes, and community-based organizations. In Vietnam, dissemination was supported by collaborations with the National Steering Committee for Natural Disaster Prevention and university labs specializing in AI and disaster research. In Singapore and Malaysia, distribution was facilitated through regional disaster management councils, ICT industry associations, and LinkedIn professional communities focusing on smart cities and disaster technologies. A total of 600 responses were received, of which 385 valid cases were retained after screening for completeness, relevance, and role-specific expertise. The final sample achieved balanced representation across stakeholder categories and countries, ensuring a robust empirical basis for examining how AI-driven flood prediction, IoT monitoring, and community readiness jointly shape disaster prevention effectiveness in climate-vulnerable regions.

IV. RESULTS

4.1. Reliability analysis

Table 1: Reliability analysis of the dependent variable. Source: (The authors, 2025)

Reliability Statistics

Cronbach's Alpha	N of Items
.743	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
DPE1	6.315	8.211	.672	.683
DPE2	6.023	8.100	.610	.704
DPE3	6.767	7.810	.678	.689
DPE4	7.098	8.096	.664	.675

Where DPE1 to DPE4 are coded for survey questions 1 to 4 of Disaster Prevention Effectiveness respectively.

In Table 1, the dependent observed variables all produced corrected item–total correlation values above the 0.3 threshold. The overall Cronbach’s alpha of 0.743 surpassed the conventional reliability standard of 0.7 and remained higher than the values that would have resulted if any item had been removed. Moreover, each observed variable recorded an alpha coefficient greater than its corresponding adjusted item–total correlation, even under hypothetical item deletions. Consequently, all four items were retained for subsequent analysis. Comparable reliability outcomes were also observed across the remaining constructs.

4.2. Exploratory factor analysis (EFA)

Table 2: Rotated Component Matrix. Source: (The authors, 2025)

Rotated Component Matrix[a]			
Component with loading factors			
1	2	3	4
DPE1 .816	FPA1 .676	EMC1 .752	CRTA1 .669
DPE2 .842	FPA2 .629	EMC2 .754	CRTA2 .685
DPE3 .850	FPA3 .683	EMC3 .691	CRTA3 .658

DPE4 .841	FPA4 .599	EMC4 .700	CRTA4 .705
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.			
a. Rotation converged in 7 iterations.			

Where the survey items FPA1–FPA4, EMCI1–EMC4, and CRTA1–CRTA4 were developed to code the two independent variables and the moderator variable, with four items allocated to each construct.

Table 2 indicates that the rotated component matrix successfully clustered the 16 observed variables into four clear factors representing the dependent variable, the two independent variables, and the moderator. Each observed variable achieved a factor loading greater than 0.5, and all items were retained in the analysis.

4.3. Multiple linear regression model

Table 3: Coefficients[a]. Source: (The authors, 2025)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	7.030	.862		4.333	.000
	FPA	.563	.745	.551	3.722	.000
	EMC	.356	.892	.347	3.568	.000

a. Dependent Variable: DPE

Where **DPE**: mean of DPE1 to DPE4; **FPA**: mean of FPA1–FPA4;
EMC: mean of EMCI1–EMC4

As shown in Table 3, the t-test produced significance (Sig.) values of .000, which are lower than the conventional alpha threshold of 0.05. This indicates that the independent variables exert a statistically significant impact on the dependent variable. Consequently, both hypotheses are supported by the empirical evidence.

4.4. Moderator analysis

Table 4: Results analysis of “Community Readiness for Technology Adoption”. Source: (The authors, 2025)

Model : 1
Y : DPE
X : FPA
W : CRTA
Sample Size: 385

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OUTCOME VARIABLE:
DPE
Model Summary

R	R-sq	MSE	F	dl1	dl2	p
.693	.480	.536	5.932	3.000	381.000	.000

Model

	coeff	se	t	p	LLCI	ULCI
constant	5.600	.775	60.006	.000	7.455	7.356
FPA	.516	.830	4.444	.000	.588	.576
CRTA	.523	.708	4.932	.000	.600	.582
Int_1	.392	.438	4.788	.000	.585	.563

Where **CRTA**: mean of CRTA1 to CRTA4

As shown in Table 4, the interaction term (Int_1) produced a p-value of 0.000, which is significantly below the 0.05 benchmark. This confirms a statistically significant interaction between community readiness for technology adoption and AI-driven flood prediction accuracy in influencing Disaster Prevention Effectiveness. The interaction coefficient of .392 indicates that higher levels of community readiness for technology adoption intensify the positive effect of AI-driven flood prediction accuracy on Disaster Prevention Effectiveness. Therefore, hypothesis H3 is empirically supported.

V. DISCUSSION

5.1. Summary results

The results from the linear regression analysis reveal that AI-driven flood prediction accuracy has the strongest influence on disaster prevention effectiveness, with a coefficient of 0.551. In comparison, IoT-based environmental monitoring coverage also contributes positively, though to a lesser extent, as reflected by its coefficient of 0.347. Additionally, the level of community readiness for technology adoption serves as a moderating factor, exerting a positive influence on the relationship between community readiness for technology adoption and disaster prevention effectiveness, with a moderation coefficient of 0.392. This analytical approach was employed to comprehensively address the research questions and elucidate the interconnections among the principal variables.

5.2. Theoretical implication

The findings strongly affirm that AI-driven flood prediction accuracy enhances disaster prevention effectiveness, but this support is nuanced. On one hand, results concur with Ali et al. (2022) and Islam et al. (2020), who argued that advanced models significantly improve forecasting reliability. Our evidence also reinforces Nearing et al. (2024), emphasizing that predictive systems provide actionable lead times essential for timely evacuation. However, this study departs from Fang et al. (2020) and Sanders et al. (2022), who equated effectiveness with statistical precision alone. The results instead highlight operational usability, aligning with Adikari et al. (2021), who stressed that imperfect but timely warnings can save more lives than technically flawless yet delayed forecasts. This research therefore contests reductionist notions of “accuracy” and supports a multidimensional definition that bridges technical precision with social usability. Thus, while broadly consistent with optimism about AI, the findings critically oppose claims that numerical accuracy alone guarantees preventive value.

The evidence partially concurs with scholarship that equates wider IoT coverage with greater disaster prevention (Narayana et al., 2024; Heimann et al., 2015). Consistent with Ray, Mukherjee and Shu (2017), broader networks do improve situational awareness. Yet, the findings critically challenge the dominant assumption, voiced by Fathy, Barnaghi and Tafazolli (2018), that sensor density itself constitutes effectiveness. Instead, this study corroborates Shah et al. (2019) and Yabe et al. (2022), showing that information quality, representativeness, and interpretability matter more than sheer quantity. The results also echo Ejaz et al. (2019), suggesting that even small, strategically positioned networks can outperform dense but poorly integrated systems. By doing so, the study unsettles techno-deterministic claims that coverage expansion automatically translates to resilience, showing instead that socio-technical alignment and usability govern preventive outcomes. Thus, while agreeing that IoT coverage is influential, the paper disputes simplistic metrics and argues for a reframing of coverage as effective monitoring rather than mere device proliferation.

The findings strongly support the moderating role of community readiness, aligning with Sinha et al. (2019) and Ryan et al. (2020), who highlighted that technological infrastructure alone cannot yield effectiveness without social willingness to act. This research concurs with Brar et al. (2022), emphasizing that trust and interpretive capacity amplify IoT benefits. However, the results diverge from Blut and Wang (2019), who narrowly equated readiness with infrastructure provision. Evidence instead confirms the broader perspective of Peng et al. (2020) and Rayamajhee and Bohara (2020), showing that even communities with limited infrastructure can exhibit high readiness if they possess trust and collective action capacity. Importantly, the study contests techno-centric arguments that assume IoT systems succeed regardless of social adoption. Instead, findings demonstrate that readiness fundamentally shapes whether monitoring outputs translate into preventive action. Thus, the research advances an argumentative stance that positions readiness as the decisive socio-technical hinge upon which IoT’s preventive value depends.

5.3. Practical implication

The findings underline that disaster governance bodies must move beyond narrow reliance on statistical benchmarks of AI-driven flood prediction and instead prioritize operational usability. While Ali et al. (2022) and Islam et al. (2020) highlight accuracy as a technical achievement, this study shows that its real value lies in early actionable alerts that save lives. Policymakers should thus institutionalize AI outputs into warning protocols, ensuring that forecast results reach communities in accessible formats and lead times (Adikari et al., 2021). This requires investments not only in model sophistication but also in communication infrastructures and training programs that help local actors interpret predictive data. Such translation of technical accuracy into operational effectiveness would prevent the "technologically precise but socially irrelevant" systems critiqued in Sanders et al. (2022).

The results suggest that governments and agencies should avoid equating IoT effectiveness with raw sensor density. Narayana et al. (2024) stress the transformative potential of dense monitoring, but this study supports Shah et al. (2019) and Yabe et al. (2022) by showing that interpretability, strategic placement, and real-time accessibility matter more than proliferation. Practical steps include prioritizing exposure-weighted sensor deployment, integrating data streams into decision dashboards, and ensuring interoperability across agencies. Investments should also be directed toward simplifying data outputs for emergency responders, since coverage that overwhelms users with noise undermines preventive capacity. Thus, "smarter" not "more numerous" sensors should guide IoT strategies, aligning with Ejaz et al. (2019) who argued for qualitative rather than quantitative expansion.

The evidence reinforces that community readiness is the decisive lever in converting IoT coverage into preventive effectiveness. This resonates with Sinha et al. (2019) and Ryan et al. (2020), showing that readiness defined by trust, literacy, and collective preparedness amplifies technological benefits. Policy implications include embedding community engagement in disaster technology projects, offering literacy programs, and fostering participatory trust-building initiatives (Peng et al., 2020). Technology rollouts must therefore be accompanied by social mobilization campaigns, subsidies for affordability, and institutional transparency to ensure legitimacy. Without such social embedding, as Blut and Wang (2019) caution, even the most advanced IoT systems may fail to trigger protective behavior. The practical message is clear: resilience depends as much on social adoption mechanisms as on infrastructural expansion.

5.4. Limitations

This study's cross-sectional survey design constrains causal inference, as perceptions of AI accuracy, IoT coverage, and readiness were captured at one point in time. The reliance on self-reported data may introduce bias, particularly in socially desirable responses regarding trust and readiness. Additionally, while the sample spanned Vietnam, Singapore, and Malaysia, cultural, institutional, and hazard-specific contexts may limit generalizability to other regions. The operationalization of "effectiveness" through perception-based measures may not fully capture real-world disaster outcomes such as mortality reduction or infrastructure protection (Mechler, 2016). Finally, the model focused on community readiness as the sole moderator, potentially overlooking other systemic variables such as government regulation, resource inequities, or cross-border governance dynamics (Tseng and Stojadinović, 2024).

5.5. Future Research Directions

Future research should adopt longitudinal and mixed-method designs to trace how AI and IoT outputs translate into actual preventive actions during disaster events. Comparative studies across diverse cultural and governance settings would clarify how readiness thresholds vary contextually (Peng et al., 2020). Expanding beyond community readiness, future work should examine institutional readiness, regulatory frameworks, and power asymmetries that may enable or constrain adoption (Blut et al., 2022). Simulation-based research could also test how sensor placement strategies or forecast lead-time variations impact real preventive outcomes. Finally, integrating emotional and behavioral dimensions of adoption, as Lee, Ramasamy and Subbarao (2025) suggest, would enrich understanding of non-rational decision-making under disaster stress, broadening the explanatory scope of socio-technical adoption models.

5.6. Conclusion

This study demonstrates that disaster prevention effectiveness is not guaranteed by technical sophistication alone but emerges through socio-technical integration. Findings confirm that AI-driven flood prediction contributes most when operationalized into actionable warnings, IoT coverage is effective when strategically embedded and interpretable, and community readiness decisively moderates whether technological infrastructures translate into resilience. Theoretically, the results support a holistic STS–TAM/UTAUT framework that bridges technical and social domains, while practically, they call for investment in interpretability, trust-building, and participatory governance. By challenging techno-deterministic assumptions, the research underscores that disaster resilience in the era of climate change requires not just "more accurate" or "more connected" systems but "more usable" and "more trusted" socio-technical pathways.

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Appendix: Survey

Table 6. Survey Design

Background Information					
1	In which country is your primary professional work located?	Vietnam	Singapore	Malaysia	Other (please specify):
2	Which professional role best represents your area of expertise?	System engineer / Data scientist	ICT infrastructure manager	Disaster management practitioner / Emergency response official	Community representative / Academic researcher
3	How many years of direct experience do you have in fields related to AI/IoT deployment, disaster risk management, or community-based resilience?	Less than 1 year	1–3 years	4–6 years	More than 6 years
4	Have you previously participated in activities related to the deployment or use of disaster prevention technologies?	Yes, frequently	Yes, occasionally	No, never	

No.	**Variables**	**Coded Sub-variables**	**Content**
1.	Disaster Prevention Effectiveness (DPE)	DPE1	Disaster prevention aims to reduce or eliminate hazard impacts before they occur, emphasizing proactive, anticipatory measures rather than post-event response (Math et al., 2015; Keim, 2018).

		DPE2	Effectiveness for governments includes economic savings and infrastructure protection, while communities emphasize protection of lives, livelihoods, and cultural assets (Mechler, 2016).
		DPE3	Broader evaluation should include improved early-warning lead times, enhance adaptive capacity, and strengthen trust in disaster governance systems (Gailmard and Patty, 2018; Wen et al., 2023).
		DPE4	True prevention effectiveness depends on end-to-end socio-technical pathways from detection and modeling to alert dissemination, community interpretation, and protective response (Haque et al., 2024; Yu and He, 2022).
2.	AI-Driven Flood Prediction Accuracy (FPA)	FPA1	AI models integrate hydrological, meteorological, and geospatial data and are assessed with metrics like RMSE, precision/recall, and AUC (Ali et al., 2022; Islam et al., 2020).
		FPA2	For prevention, “operational accuracy” forecasts that provide sufficient lead time is often more valuable than perfect numerical precision delivered too late (Sanders et al., 2022; Nearing et al., 2024).
		FPA3	Accurate, timely predictions enable evacuation planning, resource allocation, and protection of critical infrastructure (Adikari et al., 2021; Nearing et al., 2024).
		FPA4	Therefore, AI accuracy should be reframed as a multidimensional construct that bridges technical precision with operational usability (Fang et al., 2020; Nearing et al., 2024).
3.	IoT-Based Environmental Monitoring Coverage (EMC)	EMC1	IoT coverage reflects the extent/density of interconnected sensors (rainfall, river level, soil moisture, air quality) generating real-time information flows (Narayana et al., 2024).
		EMC2	Effective coverage is not mere sensor density; usability, reliability, and interpretability determine preventive value (Fathy et al., 2018; Shah et al., 2019; Yabe et al., 2022)
		EMC3	Comprehensive and reliable coverage enhances early-warning capacity and situational awareness for timely interventions such as evacuations and resource allocation (Ray et al., 2017).
		EMC4	Strategically placed, interoperable networks and exposure-weighted deployment can outperform dense but poorly integrated systems (Ejaz et al., 2019; Okafor et al., 2020).
4.	Community Readiness for Technology Adoption (CRTA)	CRTA1	Readiness includes willingness, capacity, and preparedness, shaped by perceived usefulness, ease of use, trust, and institutional support (TAM/UTAUT/DoI) (Basarir-Ozel et al., 2023).
		CRTA2	Beyond infrastructure, readiness spans socio-cultural and psychological dimensions trust, legitimacy, and willingness to act on data-driven forecasts (Blut and Wang, 2019; Son and Han, 2011).
		CRTA3	Even with limited infrastructure, communities with high trust and collective preparedness can benefit from technologies (Peng et al., 2020; Rayamajhee and Bohara, 2020).
		CRTA4	Readiness moderates the IoT coverage prevention link: low readiness can nullify benefits, whereas high readiness amplifies rapid interpretation and protective behavior (Sinha et al., 2019; Ryan et al., 2020).

Survey link: https://docs.google.com/forms/d/e/1FAIpQLSeam35FjLkoaq2zkGqtpBAM_2LPT3DPYbE-QGcT-JNr03rnVA/viewform?usp=dialog.