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Flood Crisis Mitigation in Nairobi County, Kenya: Implications of AI Technology Adoption levels

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Abstract

Flooding remains one of the most persistent disasters in Nairobi County, repeatedly destroying infrastructure, displacing communities, and straining emergency response systems. While AI technologies have the potential to transform flood crisis mitigation through predictive modelling, early warning systems, and real-time decision-support, their adoption in Nairobi, remains low and uneven. This study investigates the level of adoption of AI technologies in flood crisis mitigation in Nairobi County, highlighting the extent to which these tools are integrated into disaster management practices. The study employed a descriptive research design incorporating both quantitative and qualitative research approaches. The study targeted 219 stakeholders from state and non-state organizations involved in flood risk management in Nairobi County, with a particular focus on those engaged in integrating AI into flood mitigation strategies. A sample size of 162 respondents was selected through stratified random sampling, while 15 key informants were identified using purposive sampling. Data collection was carried out using semi-structured questionnaires and a Key Informant (KI) interview guide. Quantitative data were analysed using descriptive and inferential statistics with the aid of Statistical Package for Social Sciences (SPSS) version 28, while qualitative data were analyzed thematically s to identify patterns and generate insights. The findings reveal a significant adoption gap, with limited uptake of AI-driven solutions due to infrastructural constraints, insufficient expertise, and fragmented implementation strategies. The study recommends that Nairobi County urgently strengthens awareness, build capacity, and establish robust policy to accelerate AI adoption. By addressing these gaps, the County can shift from reactive disaster response to proactive, technology-driven resilience in the face of recurring floods.

Keywords: Adoption, Artificial Intelligence, Disaster Risk, Flood Crisis Mitigation, Predictive Modeling

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Background to the Study

Flood s are the most frequent and destructive natural disasters globally, accounting for 44% of climate-related hazards (UNDRR,2022). Their increasing frequency and intensity, driven by climate change, rapid urbanization, and poor land-use practices, continue to threaten millions of lives and cause widespread socio-economic disruption. In both developed and developing contexts, Artificial Intelligence (AI) is emerging as a transformative solution to these challenges. AI-powered systems ranging from machine learning and neural networks to predictive analytics now analyze satellite imagery, track rainfall patterns, and generate early warnings in real time, revolutionizing disaster risk reduction worldwide. (OECD,2021).

Across the globe, nations are already leveraging AI for resilience. For instance, the United States employs the National Water Model to forecast stream flows across millions of rivers using AI algorithms, while China integrates AI in dam monitoring and flood forecasting through big data and smart city systems. Such global examples illustrate how AI strengthens predictive capacity, enhances coordination and supports proactive responses in flood management.

Africa, however, continues to struggle with floods that displace communities, destroy infrastructure, and disrupt development. Limited technical expertise, weak early warning systems and inadequate institutional frameworks hinder the continent's ability to fully exploit the potential of AI in disaster management. Kenya is no exception. Nairobi County, the country's capital and economic hub, has become increasingly vulnerable to floods due to rapid urbanization, encroachment on riparian land and insufficient drainage infrastructure. Recurrent flooding in Nairobi has led to massive property damage, displacement, and public health crises, underscoring the urgent need for smarter and more proactive solutions.

Despite the availability of AI-driven tools capable of predicting, monitoring, and mitigating flood risks, their level of adoption in Nairobi County remains limited. Barriers such as infrastructural gaps, data silos, weak policy support and low awareness among institutions impede their integration into disaster management systems. These gaps raise critical questions about Nairobi's preparedness to harness AI for flood resilience. Understanding the level of adoption of AI technologies and the factors influencing it is therefore essential in shifting the county from a reactive posture to a proactive technology-driven approach to flood crisis mitigation.

Problem Statement

Despite Nairobi County's recurrent exposure to devastating floods that disrupt livelihoods, damage infrastructure, and strain emergency response systems, the integration of AI technologies in flood crisis mitigation remains limited. While AI offers predictive capabilities, real-time monitoring, and data-driven decision support that could significantly reduce flood risks, its adoption in Nairobi is hampered by gaps in awareness, infrastructural readiness, policy frameworks, and technical expertise. This slow uptake raises critical questions about the county's preparedness to harness emerging technologies for disaster risk reduction. Without deliberate strategies to accelerate the adoption of AI-driven solutions, Nairobi risks continuing cycles of reactive flood response rather than achieving proactive, resilient, and sustainable mitigation.

Objective of the Study

The objective of this study is to assess the level of adoption of AI technologies for enhancing flood crisis mitigation in Nairobi County.

Literature Review

This illustrates the literature review of AI in flood crisis mitigation. It shows knowledge gaps in theoretical and empirical literature reviews of past studies, as discussed herein.

Theoretical Review

This study was guided by two theories; Technology Acceptance Model (TAM) and Institutional Theory to frame the integration of AI technologies in flood crisis mitigation in Nairobi County. There is lack of a universal theory/model on AI use in flood mitigation. Therefore, the study used both TAM and Institutional Theory to complement each other.

Technology Acceptance Model

The Technology Acceptance Model (TAM), developed by Davis in 1989, is a theoretical framework designed to understand and predict user acceptance of technology. Rooted in the Theory of Reasoned Action (TRA), TAM was introduced to explain how perceived ease of use and perceived usefulness influence technology adoption. Perceived ease of use refers to the degree to which a person believes that using a particular system would be free of effort, while perceived usefulness describes the degree to which a person believes that using a system would enhance job performance. The model assumes that these two factors directly influence users' attitudes toward technology, which in turn impacts their intention to use it. TAM has become one of the most widely used models for studying technology acceptance, particularly in the context of Information Technology (IT) adoption (Davis, 1989). Its key proponents have expanded it to various contexts, including education, healthcare, and disaster management, focusing on how individuals interact with and adopt technology in different environments (Venkatesh et al., 2003).

Over time, TAM has been extended to include additional constructs especially in studies involving emerging technologies like Artificial Intelligence. For instance, a study by Nguyen et al. (2020) explored the acceptance of AI-based early warning systems in Vietnam. The study found that both perceived usefulness and ease of use were critical in determining the adoption of AI technologies for flood risk management. Similarly, another study by Alhawari et al. (2021) applied TAM to investigate the adoption of AI-driven predictive models in disaster response in the Middle East. The research highlighted that users' attitudes toward AI were influenced by their beliefs in its usefulness in improving the speed and accuracy of disaster forecasts. These studies demonstrate that the model is valuable in understanding the barriers and facilitators of AI adoption in disaster management, especially when assessing factors like trust, user-friendliness, and technological complexity.

While TAM has been highly influential, it is not without its critiques. One major limitation is its oversimplification of the technology adoption process by focusing primarily on two factors—perceived ease of use and perceived usefulness—without accounting for other external variables such as organizational culture, social influences, or the broader institutional context (Bagozzi, 2007). Furthermore, TAM assumes a linear and rational decision-making process that may not capture the complexity of real-world technology adoption, especially in high-stakes areas like disaster management, where emotional and psychological factors play a significant role in user decision-making. Critics also argue that TAM's focus on individual user perspectives may ignore the importance of system-wide acceptance and the integration of technologies within existing infrastructures and processes. Despite these limitations, TAM remains a foundational model, particularly when integrated with other frameworks that consider contextual and organizational factors (Venkatesh et al., 2003).

TAM provided a robust theoretical lens through which the study understood and analyzed the determinants that influenced the acceptance and integration of AI technologies in flood crisis mitigation, particularly in Nairobi County, where technology uptake was shaped by institutional readiness, user perceptions, and contextual factors. TAM offered a valuable foundation for assessing how key stakeholders—such as policymakers, disaster management personnel, and community members—perceived the usefulness and ease of use of AI tools in enhancing flood preparedness and mitigation. Perceived usefulness referred to stakeholders' beliefs that AI could improve the accuracy of flood predictions, streamline early warning systems, and optimize resource allocation, while perceived ease of use related to the accessibility and user-friendliness of AI tools, especially in informal settlements with lower technological literacy. By applying TAM, the study identified major barriers to AI adoption, including skepticism about AI's effectiveness in local contexts and difficulties in integrating new technologies with existing disaster management systems. These insights provided a basis for aligning policy frameworks with AI capabilities to strengthen flood risk reduction efforts (Venkatesh et al., 2003; Davis, 1989).

Institutional Theory

Institutional Theory was originally developed by Meyer and Rowan in 1997 and later expanded by Dimaggio and Powell in 1983. The theory posits that organizations conform to institutional pressures to gain legitimacy stability and access to resources. It's concerned with understanding how institutions defined as the formal and informal rules, norms, and practices shape organizational behavior and decision-making. One of its core arguments is that organizations are influenced by institutional pressures from their environments, such as regulatory frameworks, social expectations, and cultural norms (Scott, 2008). These pressures lead organizations to adopt practices that are deemed legitimate, regardless of whether they are the most efficient or effective. Institutional Theory assumes that organizations are not solely driven by efficiency, but also by the need to conform to institutional expectations and gain legitimacy within their field (DiMaggio & Powell, 1983). Additionally, it posits that institutional forces, such as coercive, normative, and mimetic pressures, impact how organizations operate and adopt new technologies, including AI.

Despite its widespread application, Institutional Theory has faced several critiques. Critics argue that the theory often oversimplifies the relationship between institutions and organizations, overlooking the complex dynamics and power imbalances that shape decision-making (Oliver, 1997). Another critique is its tendency to focus on conformity and legitimacy, often neglecting the agency of organizations to innovate or resist institutional pressures. Additionally, Institutional Theory has been criticized for being too static, as it tends to emphasize stability and institutionalization rather than addressing how organizations can adapt and change over time (Battilana et al., 2009). In the context of AI adoption, critics contend that the theory does not sufficiently account for the rapid pace of technological change, where organizations may act more swiftly than institutional pressures dictate, especially in sectors like disaster preparedness, where innovation is often driven by urgent needs rather than conformity to existing norms.

In the context of integrating AI technologies into flood risk reduction policies in Nairobi County, Institutional Theory offered valuable theoretical underpinnings. Nairobi's flood management policies and AI integration efforts are influenced by various institutional forces, including national disaster management policies, international aid organizations, and local governance structures. The government's policies on disaster risk reduction and AI adoption are shaped by coercive pressures from international bodies and imitative pressures from other regions where AI has been successfully integrated into flood management (Kenya Red Cross, 2023).

Empirical Literature Review

The adoption of AI technologies for flood crisis mitigation has attracted increasing scholarly attention in recent years. Numerous empirical studies have demonstrated the transformative potential of AI tools such as machine learning, remote sensing, and real-time analytics in enhancing flood prediction, early warning, and response systems. For instance, Satriani et al. (2023) conducted a comparative study of machine learning models for flood prediction and found that algorithms such as Support Vector Machines (SVM) and Artificial Neural Networks (ANN) outperformed traditional hydrological models in terms of accuracy and speed. These models have been successfully applied in various regions, offering timely predictions that are crucial for risk reduction.

Agbehadji et al. (2023) did a bibliometric study of climate-related early warning systems in Southern Africa, emphasizing on their function in strengthening resilience against climate hazards. The research underlined the rising dependence on technology-driven solutions, particularly AI, to detect and prevent climate-related calamities. It emphasized the significance of early warning systems in reducing susceptibility and enhancing readiness against climate hazards, especially in areas susceptible to severe weather phenomena. This research shifts from a broad approach, which highlighted trends in Southern Africa, to a concentrated examination of Nairobi County, Kenya, primarily assessing the use of AI in environmental catastrophe management. This study, in contrast to the bibliometric methodology of the aforementioned research, employs a localized context to examine practical applications, difficulties, and prospective frameworks for improving AI's effectiveness inside a specific metropolitan environment. This differentiation offers a more concentrated comprehension of AI's function in disaster management within Nairobi's peculiar socio-economic and infrastructural context.

Kiptum et al. (2025) examined the use of AI in Kenya for climate-related disaster management. Their study revealed that while AI applications in Nairobi County are still in the early stages, pilot projects involving predictive analytics and IoT sensors in informal settlements showed promising results in anticipating localized flooding. However, challenges to adoption persist. Ayodele et al. (2025) found that in sub-Saharan Africa, the uptake of AI in disaster management is hampered by limited infrastructure, insufficient technical capacity, and weak data-sharing mechanisms between government agencies and stakeholders. Their findings underscore the importance of institutional readiness and cross-sector collaboration in realizing AI's full potential. Mwangi et al. (2022) examined the incorporation of forecast-based action (FBA) into national disaster risk management frameworks in Kenya, specifically on drought risk management. The research assessed how early warning systems, paired with proactive measures, might boost catastrophe preparation and response to droughts. The report delineates the obstacles and insights derived from pilot programs, underscoring the need for efficient coordination, policy endorsement, and stakeholder involvement to guarantee the successful integration of forecast-based measures into national disaster risk management frameworks. .

This study contrasts with the suggested research on the role of AI applications in environmental disaster management in Nairobi County, since it largely emphasizes forecast-based actions for drought management instead of AI-driven solutions. The Nairobi research aims to examine the distinct difficulties, possibilities, and frameworks related to AI applications in disaster prevention, a topic overlooked by Mwangi et al. (2024). Their research underlined the necessity of early warning systems and human-centered interventions, whereas the emphasis of the Nairobi study will be on how AI might enhance decision-making and improve disaster planning and response at the county level. In another empirical study, Situ et al. (2025) developed a deep learning model to identify flood-prone areas in urban environments using historical weather data and land use patterns. The model, tested in Southeast Asia, achieved a high level of precision and was recommended for adaptation in other rapidly urbanizing regions facing similar risks.

These studies collectively suggest that while AI technologies offer significant promise for improving flood crisis mitigation, especially through prediction and early warning, their successful adoption depends heavily on local capacity, data availability, and institutional coordination.

Research Methodology

Research design, study area, population of the study sampling methods and methods of analysing data are discussed herein, to fulfil the research objectives.

Research Design

This study adopted a descriptive research design and a mixed-methods approach, incorporating both quantitative and qualitative research methods. The mixed-methods approach enhanced the reliability and richness of the findings, ensuring a comprehensive understanding of the subject matter (Kothari, 2004; Creswell & Creswell, 2017).

Study Area and Target Population

The research took place in Nairobi County, the capital and most populous city in Kenya, encompassing around 696 square kilometres and housing over 4.4 million people (Kenya National Bureau of Statistics [KNBS], 2023). The city's proactive strategy for using AI in disaster management, including early warning systems for floods, offers a unique chance to evaluate how AI may assist in catastrophe prediction, monitoring, and reaction. Nairobi's many neighbourhoods, ranging from prosperous regions such as Westlands to informal slums like Kibera, provide an extensive perspective on AI's potential across different socioeconomic circumstances.

The target population of this study comprised 219 stakeholders in state and non-state organizations involved in flood risk management in Nairobi County. Government Agencies, Non-Governmental Organizations (NGOs) Community-Based Organizations (CBOs) Technology Providers and AI Experts, Academia, and Research Institutions.

Sample Size and Sampling Procedure

Since the study used the survey questionnaire and Key Informant Interview (KII) guide, the study used two sampling formulas and two sample sizes. The sample size for the questionnaire survey part of the study was determined using Yamane's formula (1967), which is a widely recognized method in social science research for calculating a representative sample size from a known population. This formula yielded a sample size of 162 respondents. The study planned for 15 respondents from the population who apart from the questionnaire survey respondents as the key informants for the study, using purposive sampling technique. According to Hennink and Kaiser (2022), empirical studies often reach saturation within 9 to 17 interviews, beyond which little new information emerges. Therefore, the target sample size of the questionnaire survey was 162 respondents and the key informant guide was 15 respondents.

The research used a blend of stratified random sampling and purposive selection to guarantee a representative sample. Stratified random sample provided proper representation of diverse stakeholder groups, including inhabitants from both rich and informal settlements, emergency management authorities, AI developers, and local companies. Furthermore, purposive sampling was used to identify important informants, including policymakers, AI developers, and disaster management specialists, who hold essential expertise vital for comprehending the incorporation of AI in disaster management. The research amalgamated both methodologies to select respondents with varied viewpoints.

Data Collection Instruments

The primary data for this study were collected using two key instruments: questionnaires and key informant interview guide. These two methods complemented each other, ensuring a holistic understanding of the study's objectives.

The validity of the data collection instruments was ensured by the study supervisors, who thoroughly reviewed them to assess their relevance, clarity, and comprehensiveness in addressing the research questions and objectives. The reliability of the questionnaire was tested using the Cronbach's alpha method, which assesses the internal consistency of the instrument. A target coefficient of at least 0.7 was set, ensuring that the questionnaire produces consistent and dependable results across different respondents.

Data Analysis

Quantitative data was analysed using descriptive statistics, including frequencies, percentages, means, and standard deviations, to summarize essential attributes of the dataset. Statistical Package for the Social Sciences (SPSS) version 28 was used for data processing and analysis to guarantee precision and clarity in the presentation of outcomes. Inferential statistics, specifically bivariate regression analysis and ANOVA, were used to ascertain if significant variations exist in the perceived success of AI initiatives across various stakeholder groups, including government agencies, NGOs, technology businesses, and community leaders. In the case of qualitative data, thematic analysis was applied. This analysis technique concentrated on recognizing persistent themes, patterns, and insights pertaining to the study variables. The qualitative data results were presented narratively, supplemented by actual quotes from respondents to highlight crucial topics.

Results

Introduction

A total of 162 questionnaires were distributed to participants drawn from various institutions such as government agencies, non-governmental organizations and community-based organizations. Out of these, 121 questionnaires were received completely filled in and considered valid for analysis. This represented a response rate of 74.7% which is considered highly satisfactory for social science research. 11 key interviews out of 15 were conducted, which represented 73.3%.

Level of Adoption of AI Technologies for Enhancing Flood Crisis Mitigation in Nairobi County

The study sought to assess the level of adoption of artificial intelligence (AI) technologies for enhancing flood crisis mitigation in Nairobi County. This was examined across three key dimensions: Types of AI applied, the Absorptive Capability of institutional actors, and the Level of Integration of AI into formal strategies for enhancing flood crisis mitigation in Nairobi County. The findings are summarized in Table 1.

Table 1

Adoption of AI Technologies for Flood Crisis Mitigation in Nairobi County

	SA	A	N	D	SD	Mean	St.
Statement	F(%)	F(%)	F(%)	F(%)	F(%)		Dev
AI technologies are widely used in flood risk mitigation in Nairobi County.	56(46.3)	48(39.7)	5(4.10)	8(6.6)	4(3.3)	4.19	1.019
There is a high degree of variety in AI technologies being applied to flood risk mitigation in Nairobi County.	40(33.1)	49(40.5)	20(16.5)	9(7.4)	3(2.5)	3.94	1.011
Institutional actors in Nairobi County have the	33(27.3)	52(43)	22(18.2)	10(8.3)	4(3.3)	3.83	1.030

capacity to effectively use AI technologies for flood risk mitigation.							
There is a continuous learning process among institutional actors regarding the adoption of AI technologies for flood risk mitigation in Nairobi County.	23(19)	44(36.4)	32(26.4)	16(13.2)	6(5)	3.51	1.096
AI technologies are deeply integrated into the flood risk mitigation strategies of institutional actors in Nairobi County.	20(16.5)	49(40.5)	36(29.8)	9(7.40	7(5.8)	3.55	1.041
The integration of AI into flood risk mitigation is well-coordinated among various institutional actors in Nairobi County.	54(44.6)	48(39.7)	13(10.7)	4(3.3)	2(1.7)	4.22	0.890
Aggregate						3.873	1.015

The findings shown in Table 1 indicated that institutional actors in Nairobi County had adopted AI technologies to a substantial degree. The first statement in the table recorded a high mean of 4.19 and St Dev of 1.019. This meant that majority of the respondents either agreed or strongly agreed with the statement. Specifically, majority of the participants either agreed with this statement, signifying widespread recognition of the relevance and application of AI in managing flood risks. This suggests that AI has become a prominent tool in the flood risk management toolkit, especially for tasks such as forecasting, modeling, and real-time analysis of environmental data. The qualitative narratives reinforced these results. A county disaster management officer explained, "We are slowly realizing that AI can predict weather patterns more accurately than the tools we used before. But the challenge is making sure all our teams are equipped to understand and use these systems" (KII 1). This highlights both the promise of AI and the knowledge gaps that limit its optimal use.

In addition, the variety of AI tools used for flood risk mitigation was affirmed with a high mean score of 3.94 and St. Dev of 1.011, where majority of participants responded positively. This score reflects that majority of the respondents acknowledged the use of diverse AI tools for flood risk mitigation, including predictive analytics, machine learning algorithms, and satellite-based data systems. These findings signified strong uptake and technological diversity, suggesting a growing reliance on AI for prediction, early warning, and decision support in flood-prone areas. The implication is that institutions are not only utilizing AI but are doing so through multiple modalities, thereby enhancing the comprehensiveness and effectiveness of their responses to flood risks.

Regarding absorptive capability, the mean score for the ability of institutional actors to absorb and effectively use AI was high with a mean of 3.83 and St Dev of 1.030, with majority of respondents expressing agreement. This level of agreement points to a relatively strong foundation in technological readiness. However, the statement assessing whether institutions maintained a culture of continuous learning regarding AI adoption received a lower mean of 3.51 and St Dev of 1.096, with most of the respondents in agreement. This indicated that while institutions had the initial capacity to adopt and apply AI tools, gaps remained in maintaining and upgrading those capacities through training and professional development. This discrepancy highlights a notable weakness in the ongoing development and upgrading of institutional capacities, suggesting that while institutions may adopt AI, they often struggle to keep their human resource capacities current. Interview insights deepened this interpretation. An IT officer from a humanitarian NGO emphasized, *"The tools are here—predictive dashboards, satellite data systems—but unless people are trained and retrained, these innovations just gather dust"* (KII 5). This qualitative evidence explains the moderate scores, underscoring that institutional readiness exists but is undermined by limited investment in ongoing professional development.

With regard to the level of integration, most respondents agreed that AI integration was well-coordinated across agencies with a mean of 4.22 and St Dev of 0.890, which was the highest-rated item. This indicates that agencies working on flood risk mitigation in Nairobi County are engaging in significant levels of inter-agency collaboration, particularly around AI systems and data sharing. However, when asked whether AI technologies were deeply embedded into institutional flood mitigation strategies, responses were less enthusiastic with a mean of 3.55 and St Dev of 1.041. This suggested that while inter-agency collaboration may be functioning well, many institutions had yet to formalize AI use within core disaster response protocols and operational frameworks. Thus, while there is evidence of strong cooperation on integrating AI systems in flood mitigation, there is a lag in the formalization and institutionalization of AI within disaster management strategies. In other words, AI may be used as a tool, but it has not yet been fully incorporated into the strategic or procedural core of flood mitigation efforts. A national-level officer observed, "We're getting better at talking to each other, different agencies now share early warnings more often, and AI helps a lot. But some agencies are still lagging behind in using these tools consistently" (KII 3). This narrative clarifies that while AI has facilitated cooperation, its uneven uptake across counties limits its institutionalization into routine practice. Together, these findings suggest that while AI adoption in Nairobi County is relatively high, and inter-agency collaboration is improving, sustained absorptive capacity and stronger formal integration into disaster management policies are needed to ensure long-term effectiveness.

Regression Analysis of the effect of Adoption of AI Technologies on Enhancing Flood Crisis Mitigation in Nairobi County

Bivariate regression analysis was subsequently carried out to find out whether the level of adoption of AI technologies significantly enhanced flood crisis mitigation in Nairobi County. The results are presented in Table 2.

Table 2

Respondents' Views on Level of Adoption of AI Technologies on Enhancing Flood Crisis Mitigation in Nairobi County

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	0.327	0.481		0.678	0.499
Level of AI Adoption	0.765	0.123	0.496	6.23	0.000

R	.496a	df	1, 119		
R Square	0.246	Mean Square	25.475, 0.656		
Adjusted R Square	0.240	F	38.811		
Std. Error of the Estimate	0.81018	Sig.	.000b		
a Dependent Variable: Flood Mitigation					

The regression analysis results on the impact of AI adoption on flood crisis mitigation in Nairobi County show a moderate positive relationship, with a correlation coefficient (R) of 0.496 and an R^2 of 0.246, indicating that 24.6% of the variation in flood mitigation effectiveness is explained by the level of AI adoption. The ANOVA results further show that the model was statistically significant ($F = 38.811$, $p = 0.000$), and the unstandardized coefficient for AI adoption was $B = 0.765$ ($t = 6.23$, $p = 0.000$) and positive, suggesting that higher AI adoption leads to significantly improved flood mitigation outcomes. The standardized beta of 0.496 confirms AI adoption as a strong predictor. Although the constant term (0.327) was not statistically significant ($p = 0.499$), the overall model fit was robust. These findings highlight AI's positive contribution to flood mitigation, though the moderate R^2 suggests that additional factors also influence outcomes, pointing to the need for more comprehensive approaches involving infrastructure, policy, and emergency response systems.

The qualitative findings provided important context for these results. A county disaster management director observed, *"We are slowly realizing that AI can predict weather patterns more accurately than the tools we used before. But the challenge is making sure all our teams are equipped to understand and use these systems"* (KII 1). This statement reinforced the quantitative evidence, showing that while AI has strong predictive potential, institutional capacity gaps in training and absorptive readiness limit its full impact. Similarly, a national policy officer emphasized uneven adoption across regions: *"We're getting better at talking to each other, different agencies now share early warnings more often, and AI helps a lot. But some counties are still lagging behind in using these tools consistently"* (KII 4). These perspectives highlighted geographical and institutional disparities, explaining why the R^2 remained moderate despite significant statistical effects.

The findings from both the quantitative and qualitative data align with trends identified in global and regional literature on the use of AI in disaster risk reduction. Kumar et al. (2023) argued that machine learning and other AI models provide superior predictive capabilities in flood management compared to traditional forecasting techniques. This assertion is directly supported by the high agreement rates on the use and diversity of AI tools in this study, which illustrate the shift from conventional methods to AI-enhanced systems in Nairobi County.

Additionally, Agbehadji et al. (2023) emphasized that AI-driven early warning systems significantly improve institutional responsiveness and community preparedness, especially in urban African contexts. The positive ratings for coordination and communication among agencies in Nairobi County reflect similar outcomes. These high coordination scores suggest that the adoption of AI is already enhancing cross-agency workflows and decision-making in line with international best practices.

The study's findings also align with concerns raised by African researchers about persistent implementation challenges. Ayodele et al. (2022) reported that across sub-Saharan Africa, weak digital infrastructure, fragmented institutional arrangements, and low AI literacy remain serious impediments to the success of AI-based disaster mitigation strategies.

These challenges mirror the low mean scores recorded for continuous learning and strategic embedding in Nairobi institutions. Similarly, Kiptum et al., (2025) observed that although Nairobi has shown leadership in adopting environmental monitoring technologies, significant gaps remain in ensuring system interoperability and institutional uptake. This reflects the current study's finding that while AI is present and somewhat coordinated, it is not yet deeply embedded into institutional strategies or operational procedures.

Conclusion

Based on the findings, the study concludes that the adoption of AI technologies for flood crisis mitigation in Nairobi is still at nascent stage, with limited use mainly concentrated in pilot projects and research initiatives. The level of adoption of AI technologies had a moderate impact on flood crisis mitigation in Nairobi County. The moderate adoption of AI tools such as machine learning, GIS mapping, and data analytics, signal growing awareness of digital solutions in disaster management. The uptake is hindered by infrastructure gaps, high implementation costa, limited technical expertise, and inadequate policy frameworks. Inadequate resources, inconsistent policies, and unequal technical capacity hinder uniform integration, highlighting the need for broader investment, training, and institutional support.

Recommendations

In the light of the foregoing findings, the study makes the following recommendations for practice and policy on enhancing the level of adoption of AI technologies for flood crisis mitigation in Nairobi County. Nairobi County could consider providing regular training and capacity-building programs for disaster management staff, engineers, and community responders on AI-based flood monitoring and forecasting tools. Additionally, partnerships between government agencies, local universities, and tech firms to pilot AI-driven flood projects in flood-prone wards could be encouraged. Subsequently, a county-level adoption framework within the disaster risk reduction (DRR) policy to guide AI integration in flood management could be developed. Meanwhile, allocation of dedicated budget lines in county disaster preparedness funds for AI technology acquisition and maintenance could be considered.

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