Integration of AI tools into management and governance of humanitarian projects in conflict-affected North-West Nigeria

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Abstract
Humanitarian projects in conflict zones face extreme complexity caused by, inter alia, volatility, fragmentation, and accountability pressures. Such complexity often renders conventional project implementation approaches inadequate. This study, focused on the conflict zone of North-West Nigeria, investigated the extent to which artificial intelligence (AI) tools can enhance the effectiveness of management governance and governance of humanitarian projects. Grounded in sociotechnical systems (STS) theory, the study surveyed 300 project personnel across Kebbi, Katsina, and Jigawa States, and conducted interviews with 25 of the personnel. Statistical analysis of the quantitative data from the survey found that the adoption of AI tools had a statistically significant correlation with project management effectiveness (β = .46, p < .001), with organisational readiness and ethical governance found to serve as significant partial mediators. The qualitative findings from the interview data identified AI tools' positive roles in project management and governance—through support for (human-led) decision support, transparency, and anticipatory governance—but also revealed tensions around equity, attentional displacement, and the marginalisation of national actors.

Keywords
artificial intelligence (AI), AI tools, humanitarian projects, project management, project governance, conflict zones, sociotechnical systems (STS) theory, North-West Nigeria, Kebbi, Katsina, Jigawa

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1. Introduction

Humanitarian-project implementation in conflict-affected regions constitutes a challenge of paramount importance, requiring the simultaneous navigation of uncertainty, operational insecurity, and intensified donor accountability pressures. In North-West Nigeria, specifically Kebbi, Katsina, and Jigawa States, a complex mix of armed banditry, farmer–herder conflicts and cross-border criminality has created a humanitarian crisis with severe access constraints (UNHCR, 2023). Within this volatile environment, project managers are tasked with delivering humanitarian assistance while also ensuring robust governance, adaptive risk management, and verifiable transparency.

Artificial intelligence (AI) tools have proven to be transformative in mainstream project management and governance, offering predictive analytics, real-time monitoring, and automated reporting. However, the application and empirical examination of AI use for project management and governance in conflict-affected contexts remain nascent, particularly in Sub-Saharan Africa (Vinuesa et al., 2020). Critical questions persist regarding AI tools' potential roles in environments where institutional fragility, ethical risks, and digital divides are pronounced (Meier, 2015).

This study examined AI use for project management and governance by humanitarian projects operating in conflict-affected states of North-West Nigeria. The data collection and analysis focused on empirically investigating how AI adoption functions in such projects not merely as a technical tool, but also as a project management and governance mechanism that shapes effectiveness, accountability, and risk resilience.

2. Literature review

Use of AI tools in project management and governance

An important evolution in scholarship on AI in project management and governance is the reconceptualisation of AI tools from being automation engines to being partners to human decision-makers. Marnewick and Marnewick (2020) explain how AI applications can enhance project management and governance by fostering improvements in data integrity, in auditability, and in strategic oversight, particularly in complex projects. Other literature emphasises AI's potential for dynamic resource reallocation in response to changing project conditions, a capability that is particularly valuable in unstable environments (KPMG, 2020; Müller et al., 2022). Such studies shift the focus from replacing human judgment to augmenting it within structured frameworks. In the management and governance of humanitarian projects, the AI tools used typically include applications supporting the following four functions: predictive analytics; monitoring and evaluation (M&E); reporting and accountability; and decision support.

Predictive-analytics tools

These tools process multidimensional data, including conflict-incident reports, weather patterns, market prices, and population-displacement metrics, to forecast risks before they materialise. For instance, in North-West Nigeria, organisations use machine learning models trained on historical banditry patterns to predict high-risk periods for staff movements and supply convoys (Meier, 2015).

Monitoring and evaluation (M&E) systems

These systems employ computer vision and natural language processing (NLP) to analyse satellite imagery, social media, and field reports, enabling real-time tracking of project implementation. The UN's use of AI-augmented damage assessment in conflict zones demonstrates how these tools can enhance situational awareness while reducing the exposure of personnel to security risks (UN OCHA, 2022).

Reporting and accountability platforms

These platforms automate data aggregation from disparate field sources into standardised donor dashboards, creating auditable trails of resource allocation and expenditure. These systems address the intensified accountability pressures that humanitarian actors face while potentially introducing new tensions around data simplification.

Decision-support systems

These systems integrate these capabilities to present actionable recommendations to human decision-makers, such as optimal resource reallocation when security incidents disrupt planned distributions.

Particularities of humanitarian-project management and governance in conflict settings

Project management and governance in humanitarian projects in conflict settings are often fundamentally distinct from what is required in commercial projects. Humanitarian projects are much more likely to be characterised by, inter alia, dynamic ethical imperatives, highly politicised operating environments, and acute security risks (Betts et al., 2015). In conflict zones, information asymmetries and rapid contextual shifts render traditional, linear project tools inadequate (UN OCHA, 2022). Scholars increasingly advocate for adaptive, data-informed project management and governance mechanisms that prioritise resilience and stakeholder accountability over rigid plan adherence (Maxwell et al., 2022; Sandvik et al., 2014). Barnett (2023) highlights the tension between the need for rapid adaptation in conflict settings and the requirements for accountability and transparency demanded by donors and affected communities. The value proposition of AI in humanitarian project management and governance is AI tools' ability to assist human decision-makers in addressing the above-mentioned challenges in the following ways:

- *Information asymmetry*: Humanitarian actors often lack real-time visibility of rapidly changing conditions, and AI-enabled sensing and analysis can reduce this asymmetry.
- *Anticipatory capacity*: Traditional project tools are retrospective, while AI tools' predictive capabilities enable proactive rather than reactive management and governance.
- *Accountability and transparency*: Donors and affected communities demand frequent and clear evidence of resource use, and AI-enabled traceability systems can help to provide this (while, as seen in the next sub-section, potentially introducing new forms of surveillance that require careful ethical navigation).

Ethical complexities of AI use in project management and governance

As stated above, AI-enabled systems can strengthen project accountability and transparency. Among other things, AI tools support enhanced data accuracy, real-time compliance-tracking, and traceable decision logs (Bannister & Connolly, 2020; Müller et al., 2022). However, this integration can introduce ethical risks, including risks of algorithmic bias, data protection vulnerabilities, and the potential for "accountability washing", where human responsibility is obscured (Stahl et al., 2016). These risks necessitate robust, context-specific governance safeguards—a concern reflected strongly in African digital ethics discourse (Bah et al., 2024; Eke et al., 2023). Recent scholarship emphasises the importance of contextually appropriate AI that respects local knowledge systems and addresses power imbalances in humanitarian settings (Fayehun et al., 2023; Mulder, 2023). Mulder (2023) highlights how externally driven localisation can create legitimacy paradoxes, where local actors must navigate contradictory demands—a dynamic that risks being amplified when AI tools are introduced without adequate attention to local ownership and ethical safeguards.

Nigerian empirical context: Adoption amidst structural constraints

Emerging Nigerian empirical studies document a growing, yet uneven, adoption of AI tools in project management and governance. Some studies highlight persistent constraints, including critical infrastructure gaps (e.g., unstable power, limited internet), skill deficits, and socio-cultural hesitancy (Adeleke et al., 2023; Akinola & Ogunbayo, 2024). Other studies, such as that by Lawal et al. (2024), demonstrate AI's positive impact on coordination in Nigerian projects. But there is a scarcity of focused research on its application within the country's humanitarian sector, particularly in conflict zones. This underscores the novelty and contribution of the present study, which builds on recent Nigerian scholarship examining digital innovation pathways in non-governmental sectors.

3. Theoretical lens and conceptual model

This study was guided by sociotechnical systems (STS) theory, which posits that organisational outcomes are optimised when social (human, organisational) and technical (technology, tools) subsystems are jointly designed and mutually adaptive (Trist, 1981). This theory, which places a strong emphasis on understanding the mediating roles of social and technical dimensions, offers a lens for exploring AI's impact on project effectiveness that is not direct but mediated by social subsystems: namely, organisational readiness (skills, infrastructure, culture) and ethical governance (policies, oversight, values). This framework moves beyond a technocentric view to analyse AI as an embedded element within a complex organisational and ethical landscape.

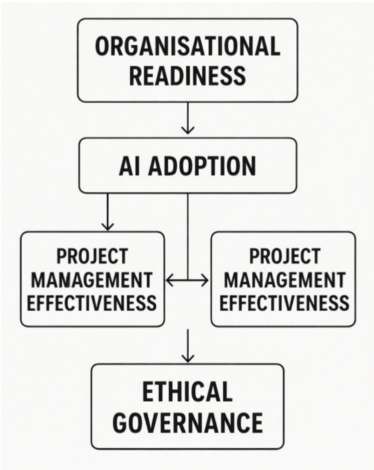
The conceptual model developed to guide the study, as illustrated in Figure 1, is grounded in STS theory and proposes that AI adoption influences project management and governance effectiveness, both (1) directly and (2) indirectly through two mediators (organisational readiness and ethical governance). The model thus posits three parallel pathways (one direct, two indirect) for the influence of AI adoption:

- *A direct pathway* from AI adoption to project management effectiveness, representing the pure technical contribution of AI tools, enhanced data analytics, predictive capabilities, and automated reporting that improve decision-making regardless of organisational context.
- *An indirect pathway through organisational readiness*, capturing how AI adoption prompts investments in staff training, technological infrastructure, and supportive organisational cultures, which are investments that independently enhance project outcomes.

- *An indirect pathway through ethical governance*, reflecting how AI adoption necessitates the development of data protection protocols, bias detection procedures, human oversight mechanisms, and accountability frameworks, which are safeguards that improve project effectiveness by preventing errors and ensuring responsible action.

This multi-pathway model reflects the core insight of STS theory: technology and social systems co-evolve, and optimal outcomes require joint optimisation of both subsystems. The model guides both the measurement strategy (identifying appropriate constructs for each pathway) and the analytical approach (testing mediation through bootstrapped confidence intervals).

Figure 1: Conceptual model



4. Methodology

Research design

A convergent parallel mixed-methods design was employed, where quantitative and qualitative data were collected concurrently, analysed independently, and integrated at the interpretation stage to provide comprehensive validation and richer insight (Biedenbach & Müller, 2023; Creswell & Clark, 2017). This design is particularly suited to exploring complex phenomena where numerical trends require contextual, narrative explanation.

Sample and data collection

Quantitative strand

A sample of 300 humanitarian project personnel (100 each from Kebbi, Katsina, and Jigawa) was obtained via stratified random sampling based on organisation type (UN agency, international NGO, national NGO) and project role (managerial, technical, field). Participants completed a structured survey questionnaire administered electronically and in-person. The response rate was 72%. The full questionnaire is provided in Appendix A.

Qualitative strand

Twenty-five key informant interviews were conducted with project managers (n = 12), donor representatives (n = 6), and ICT officers (n = 7), selected through purposive sampling to capture diverse, expertise-based perspectives. Interviews followed a semi-structured protocol (Appendix B) and lasted 45–75 minutes.

Measurement and variables

All constructs were measured using validated 5-point Likert scales (1 = Strongly Disagree, 5 = Strongly Agree). Instruments were pre-tested with 30 humanitarian workers who were not in the final sample, leading to minor wording adjustments.

Independent variable: AI adoption (8 items; α = .87)
AI adoption was measured as the extent to which organisations use AI tools for humanitarian project management functions. The scale assessed the use of AI for predictive analytics, real-time monitoring, automated reporting, and decision support. Sample items were: "Our organisation uses AI tools for predictive risk analysis" and "We utilise machine learning to anticipate supply chain disruptions".

Mediating variables
Organisational readiness (6 items; α = .82) was conceptualised as institutional capacity to absorb, integrate, and sustain AI technologies. The scale assessed four dimensions: human capital readiness (staff skills and training), technological infrastructure (hardware, software, connectivity), cultural readiness (openness to innovation), and resource commitment (budget and leadership support). A sample item was: "Our staff have adequate training to use AI tools effectively".

Ethical governance (6 items; α = .80) was defined as institutional mechanisms ensuring AI systems operate in accordance with humanitarian principles, data protection standards, and accountability requirements. The scale captured policy frameworks, data stewardship, algorithmic accountability, and human oversight. A sample item was: "We have clear protocols for ethical review of AI-driven decisions".

STS theory justifies these as mediators because AI's governance impact is hypothesised to operate through the social and structural conditions, readiness, and ethics that enable technology to translate into improved outcomes (Trist, 1981). Both scales demonstrated acceptable convergent and discriminant validity in confirmatory factor analysis.

Dependent variable: Project management effectiveness index (PMEI)
The dependent variable was a composite index calculated as the mean of three standardised sub-scales: risk management (5 items, α = .85), governance and accountability (6 items, α = .88), and transparency and donor confidence (4 items). With regard to validation, all items loaded > 0.70 on a single factor in principal component analysis, explaining 68% of variance, confirming the index's construct validity.

Data analysis strategy
Quantitative analysis
The quantitative analysis was conducted using SPSS/Stata. Descriptive statistics and scale reliability were computed. Common method bias (CMB) was assessed using Harmon's single-factor test, which showed the first factor explained 38.2% of variance (< 50% threshold), suggesting that CMB was not a severe threat (Podsakoff et al., 2003). Pearson correlation examined bivariate relationships. Hierarchical multiple regression tested the predictive model. Mediation analysis used the bootstrapping method (Preacher & Hayes, 2008) with 5,000 resamples to test indirect effects. One-way ANOVA explored inter-state differences.

Qualitative analysis
For the qualitative analysis, interviews were transcribed and subjected to thematic analysis following Braun and Clarke's (2006) six-phase approach using NVivo 14, employing a hybrid inductive-deductive approach to identify patterns related to AI's governance role.

Ethical considerations
The study received approval from the University of Uyo's Research Ethics Committee. Informed consent was obtained from all participants, with special measures to ensure confidentiality and security given the conflict-affected context. Data was anonymised and stored securely.

5. Findings and analysis

Descriptive statistics and scale reliability

Table 1 presents descriptive statistics for all study variables. All constructs demonstrated high internal consistency, with Cronbach's Alpha values well above the 0.70 threshold. The mean scores provide insight into the current state of AI adoption and related organisational factors in North-West Nigeria's humanitarian sector.

Table 1: Descriptive statistics and reliability (*n* = 300)

Variable	Mean (*M*)	*SD*	Cronbach's alpha	Skewness	Kurtosis
AI adoption	3.54	0.83	0.87	-0.32	-0.45
Risk management	3.75	0.78	0.85	-0.41	-0.38
Governance and accountability	3.75	0.77	0.88	-0.38	-0.41
Organisational readiness	3.42	0.81	0.82	-0.28	-0.52
Ethical governance	3.38	0.84	0.80	-0.25	-0.48

Significance of these statistics for humanitarian practice

- AI adoption (*M* = 3.54) indicates that, on average, respondents moderately agree that their organisations use AI tools. Adoption is underway but not yet universal. The standard deviation of 0.83 shows reasonable variation; some organisations are further ahead, others are behind.
- Risk management and governance and accountability (both *M* = 3.75) received the highest scores, suggesting that respondents generally agree that their organisations demonstrate competent risk management and robust governance practices. These traditional humanitarian competencies remain strong even as AI adoption progresses.
- Organisational readiness (*M* = 3.42) falls between "Neutral" and "Agree", suggesting that while organisations have made progress in building capacity for AI, significant gaps remain in skills, infrastructure, or cultural readiness. This aligns with qualitative findings about training needs and infrastructure constraints.
- Ethical governance (*M* = 3.38) is the lowest mean, indicating that ethical frameworks for AI, data protection protocols, bias mitigation procedures, and human oversight mechanisms are the least developed area. This finding is particularly significant given ethical governance's role as a mediator of AI's effectiveness.
- All skewness and kurtosis values fall within acceptable ranges (-1 to +1), confirming that the data are approximately normally distributed and suitable for parametric statistical tests.

Results from correlation analysis

Table 2: Pearson correlation matrix

Variable	1	2	3	4	5
AI adoption	1				
Risk management	.62**	1			
Governance and accountability	.58**	.71**	1		
Organisational readiness	.49**	.52**	.54**	1	
Ethical governance	.46**	.50**	.56**	.61**	1

**** p < .001. All correlations are significant at the 0.001 level.**

What these statistical relationships reveal about humanitarian practice

The correlation matrix shows that all five variables move together; organisations that are strong in one area tend to be strong in others. But the pattern of relationships tells a more nuanced story:

- AI adoption ↔ risk management (.62): Organisations using AI more extensively report a significantly stronger ability to anticipate and manage risks. This suggests that AI's predictive capabilities are translating into tangible risk management benefits. A project manager in Katsina explained: "The AI system analyses patterns from the past five years and gives us risk probabilities for each road each day. We now move from reaction to anticipation."
- AI adoption ↔ governance and accountability (.58): Higher AI adoption is associated with more robust governance practices. Organisations embracing AI tend to have stronger documentation, oversight, and accountability mechanisms, or perhaps the AI tools themselves enhance these governance functions.
- AI adoption ↔ organisational readiness (.49): Organisations with greater AI adoption have invested more in staff skills, infrastructure, and supportive cultures. This makes intuitive sense: you cannot use what you are not prepared to implement.
- AI adoption ↔ ethical governance (.46): The positive but slightly weaker correlation suggests that while AI-adopting organisations have developed some ethical frameworks, ethics may be lagging behind technology, which is a concern given the risks that AI poses in humanitarian contexts. A national NGO director observed: "Many organisations adopt AI without building readiness or ethics first. They get the technology because donors fund it, but they have not trained staff or established protocols."
- Risk management ↔ governance and accountability (.71): The strongest correlation reveals that organisations that are good at managing risks are also strong in governance. These capabilities reinforce each other: both require disciplined information flows and decision protocols.
- Organisational readiness ↔ ethical governance (.61): Organisations investing in technical capacity also tend to invest in ethical safeguards. This is encouraging: readiness and ethics appear to develop together rather than one developing at the expense of the other.

Results from hierarchical regression and mediation analysis

Table 3: Hierarchical regression predicting project management effectiveness

Model	Predictor	β	*t*	*p*	R^2	ΔR^2	*F change*
1	**AI adoption**	**0.46**	**9.12**	**< .001**	**0.28**	**0.28**	**81.4****
2	AI adoption	0.35	6.94	< .001	0.41	0.13	42.1**
2	Organisational readiness	0.29	5.87	< .001			
3	AI adoption	0.27	5.12	< .001	0.53	0.12	36.8**
3	Organisational readiness	0.22	4.45	< .001			
3	Ethical governance	0.21	4.26	< .001			

****Model 3: $F(3, 296) = 111.4$, $p < .001$**

What hierarchical-regression findings reveal

- Model 1 (AI adoption alone): AI adoption alone explains 28% of the differences in project management effectiveness between organisations. This is substantial, comparable to knowing that a student's study hours explain 28% of why some students get higher grades. The standardised coefficient (β = .46) means that when AI adoption increases meaningfully, project effectiveness increases by nearly half a standard deviation, a practically significant impact.
- Model 2 (adding organisational readiness): When organisational readiness enters the picture, AI's direct contribution drops from .46 to .35, while readiness itself contributes significantly (.29). Together, they explain 41% of effectiveness differences, a 13% improvement. This tells us the

following: Part of why AI improves effectiveness is because organisations that adopt AI tend to be more ready, and readiness itself matters. But AI still contributes beyond readiness.

- Model 3 (adding ethical governance): Adding ethical governance increases explained variance to 53%, meaning that these three variables together account for over half of why some organisations manage projects more effectively than others. AI's coefficient drops further to .27, while both mediators remain significant (.22 and .21). This reveals the following: AI's influence on effectiveness runs partly through strengthening organisational readiness and ethical governance. The technology does not simply work on its own; it enables and is enabled by these human and structural factors.

Table 4: Bootstrapped-mediation effects

Effect type	Path	β	Boot *SE*	95% *CI* lower	95% *CI* upper
Total effect	AI adoption → PMEI	0.46	0.05	0.37	0.55
Direct effect	AI adoption → PMEI	0.27	0.05	0.17	0.37
Indirect effect 1	AI adoption → organisational readiness → PMEI	0.08	0.03	0.03	0.14
Indirect effect 2	AI adoption → ethical governance → PMEI	0.06	0.02	0.02	0.11

What mediation-analysis findings reveal

The mediation analysis moves beyond asking "does AI work?" to answer the more important question: "How does AI actually improve humanitarian project management in conflict zones?" The core finding is as follows: AI's value flows through two distinct kinds of pathways, direct and indirect, and understanding this distinction matters profoundly for practice:

The direct pathway (β = .27): The technology itself helps: Consider a project manager in Katsina who receives an AI-generated alert predicting road closures based on recent bandit activity patterns. She reroutes a food convoy, avoiding a potential attack. This is AI working *directly*, since the technology's analytical capability produced actionable information that human judgment alone might have missed. The direct effect of .27 represents this pure technical contribution: better data, faster pattern recognition, and more accurate predictions. This pathway accounts for approximately 59% of AI's total observed impact.

The indirect pathway through organisational readiness (β = .08): AI forces capacity building: Before that project manager can act on the AI alert, her organisation had to invest in training staff to interpret AI outputs, upgrade internet connectivity, and create response protocols. These investments in readiness, prompted by AI adoption, independently enhance project management beyond the AI tools themselves. This pathway accounts for about 17% of AI's total effect. A national NGO programme manager described this dynamic: "When we first got the AI reporting system, we realised our staff did not know how to use it. We had to invest in training. We realised our internet in field offices was too slow, we had to upgrade. The AI adoption itself forced us to become more capable. And now that we have those capabilities, our whole operation runs better, not just the AI part."

The indirect pathway through ethical governance (β = .06): AI demands accountability: A different project manager receives an AI recommendation to prioritise certain villages for food distribution. Before acting, she consults an ethics protocol requiring human review. She notices that the model may be biased because it lacks data from communities beyond mobile network coverage. She overrides the recommendation and sends a field team to verify needs directly. This pathway, accounting for about 13% of AI's effect, represents how AI necessitates oversight mechanisms that themselves improve outcomes by preventing mistakes. A project manager explained: "We had an ethics protocol requiring human review of all AI recommendations. That protocol caught a major error: the AI recommended deprioritising a community because its data was incomplete, but our field staff knew displaced families had arrived there. Without the protocol, we would have followed the AI and created harm. The 13% mediation effect, that is what saved us."

The combined insight: Together, the indirect pathways account for 30% of AI's relationship with project effectiveness. This is not a statistical curiosity but a practical revelation: when a humanitarian organisation adopts AI, nearly one-third of the benefit comes not from algorithms alone but from how adopting AI transforms organisations, making them more capable, more disciplined, and more accountable.

Results from state-level comparison

One-way ANOVA revealed no statistically significant differences in AI adoption levels across the three states: Kebbi (M = 3.48, SD = 0.79), Katsina (M = 3.57, SD = 0.85), Jigawa (M = 3.57, SD = 0.86); $F(2, 297)$ = 0.56, p = .57. However, understanding what "AI adoption" means in practice requires understanding each state's unique conflict dynamics.

Kebbi State (M = 3.48)

Kebbi's challenges are dominated by cross-border criminality along the Niger frontier and armed banditry affecting agricultural communities. Project managers use predictive analytics primarily to anticipate farming season violence and model safe corridors for cross-border supply chains. A logistics coordinator explained: "In Kebbi, our biggest risk is unpredictability during planting and harvest seasons. The AI tools analyse patterns from the past three years, which villages were attacked, when, and what the security response was, and give us probabilities we can plan around." The slightly lower mean may reflect more rural, harder-to-reach areas where connectivity for real-time AI applications remains inconsistent.

Katsina State (M = 3.57)

Katsina faces the most intense and sustained banditry activity. Project managers emphasise AI's role in real-time threat assessment and staff security. A project manager described this role as follows: "In Katsina, we cannot afford to be reactive. The AI system integrates data from security agencies, community networks, and social media to update risk scores for each operational area daily. When the risk score crosses our threshold, we do not move staff that day, regardless of planned activities."

Jigawa State (M = 3.57)

Jigawa's conflict dynamics include farmer–herder tensions and spillover violence, but with more predictable patterns. Project managers report using AI primarily for resource allocation efficiency and donor reporting, rather than acute security prediction. An ICT officer explained: "Our focus is making sure limited resources reach the maximum number of people. The AI helps us analyse needs assessment data across 200+ communities and optimise where we send mobile health teams. It also automatically generates donor reports, freeing staff for field monitoring."

What the statistical homogeneity means

The finding of no significant differences tells us something important: AI adoption is driven more by organisational factors than location-specific conditions. International NGOs and UN agencies deploy similar tools across their entire portfolios. However, this homogeneity masks profound inequities *within* states. A national NGO director in Katsina stated: "The average of 3.57 in Katsina combines international NGOs scoring 4.5 and national NGOs scoring 2.5. The mean is mathematically correct but practically misleading. The real story is not about states; it is about who has resources and who does not."

Integration of survey (quantitative) findings with interview (qualitative) findings

This section weaves together quantitative patterns with qualitative evidence to explore how AI functions as a project management and governance tool in the lived experience of humanitarian actors.

Understanding the AI adoption-effectiveness relationship (β = .46)

The quantitative analysis established that AI adoption significantly predicts project management effectiveness. But what does "more effective" mean in practice? Qualitative data reveals three concrete mechanisms.

Mechanism 1: Anticipation replaces reaction

In the words of a project manager in Katsina: "Before AI, we were always responding to crises after they happened. Now we receive risk forecasts that let us act before the crisis. Last month, the AI predicted a

65% probability of attack on the Funtua road based on patterns we had never noticed, attacks spike three days after full moons. We rerouted our convoy. Three days later, that road was attacked. The .46 effect size, that is us. That is supplies arriving safely because we anticipated." A logistics coordinator in Kebbi added: "Our AI flagged that heavy rains predicted for the following week, combined with increased bandit activity, would likely close our main supply route. We had three days' warning. We moved two weeks of food into our warehouses before the road became impassable. The statistics show AI predicts effectiveness; I can tell you exactly what that looks like: children eating because food arrived on time."

Mechanism 2: Decision quality improves
An ICT officer explained: "The AI does not make decisions; it gives us better information for decisions we must make anyway. When deciding which communities to prioritise for mobile health teams, the AI analyses needs data from 200+ locations and flags where malnutrition is rising fastest. We still make the final decision, but with information we could never assemble manually."

Mechanism 3: Accountability becomes auditable
In the words of a donor representative, addressing the relevance of AI to donor confidence: "When partners use AI, they can show us why they made decisions. They can say, 'We rerouted because our model showed X, Y, and Z factors converging.' This creates an audit trail for adaptive management. We trust partners more when we understand their logic."

Explaining the mediation pathways
The mediation analysis revealed that organisational readiness and ethical governance account for 30% of AI's effect. Qualitative data explains why.

The readiness pathway: AI forces capacity-building
A national NGO programme manager said: "We had to invest in training. We realised we needed someone who understood data, we hired a new staff member." An ICT officer confirmed: "Organisations cannot just buy AI software and expect magic. You need infrastructure. You need skills. You need leadership that supports innovation. The organisations in our survey with high readiness scores are the ones where AI actually works."

The ethics pathway: Trust requires safeguards
A project manager explained: "Early in our AI use, we had an incident. The system recommended prioritising certain villages based on malnutrition data. But the data was incomplete, it missed newly displaced families. Because we had an ethics protocol requiring human review, a staff member caught the error. The protocol saved us. Now we see ethical governance not as a constraint but as something that makes AI work better." A donor representative emphasised: "We will not fund AI projects without strong ethical frameworks. Why? Because when things go wrong, and they will, someone must be responsible. If an organisation cannot show us how they oversee AI, how they protect data, how they prevent bias, we cannot take the risk."

The central tensions: What the numbers cannot show
Across all interviews, the following tensions emerged that quantitative data alone cannot capture:

Empowerment and marginalisation: An international NGO programme manager celebrated AI's benefits, while a national NGO director stated: "Meanwhile, we cannot afford these tools. In coordination meetings, international partners bring AI-generated maps and forecasts. We bring our community knowledge. Guess whose information is treated as credible? The technology creates a hierarchy where those with AI are heard and those without are silenced, even when we know the context better."

Efficiency and burden: While a donor representative praised the AI dashboards, a field officer described the same dashboards differently: "I spend more time looking at my phone entering data than looking at the community. The system demands information, and I provide it, but I am not sure the community benefits from my attention being on the screen rather than on them."

Clarity and obfuscation: An ICT officer emphasised AI's transparency, while a programme manager cautioned as follows: "But the dashboard cannot show us whether people felt respected during distribution. It cannot show community tensions. We risk optimising for what the machine can measure while ignoring what matters."

The human-in-the-loop imperative: A field officer offered this reflection: "The algorithm can suggest where needs are greatest. It can calculate efficiency. It can optimise resources. But it cannot understand dignity. It cannot know that in this community, because of their history, distributing food in the morning rather than afternoon matters. It cannot feel the tension in a conversation and decide to pause. These are human things. The AI is a tool. But the work itself, the work of being with people in crisis, that is human work. It must remain human work."

6. Discussion

Theoretical contribution: AI as embedded governance infrastructure

The central theoretical contribution is support for the reconceptualisation of AI as not a stand-alone technical tool, but as an embedded project management and governance infrastructure whose effects are realised through organisational and ethical subsystems. First, it challenges technocentric narratives treating AI as a direct solution to management challenges. The finding that 30% of AI's effect operates through readiness and ethics demonstrates that technology alone is insufficient. Organisations investing in AI without concurrent investment in capabilities and safeguards capture only about 70% of AI's potential value. Second, it specifies mechanisms through which AI influences governance outcomes: anticipatory capacity (predictive analytics enabling proactive risk management), accountability infrastructure (automated reporting creating auditable decision trails), and decision support (AI augmenting rather than replacing human judgment). Third, it reveals the double-edged nature of AI-enabled governance. While informants affirmed AI's value, they also identified tensions: measurable outputs displacing meaningful outcomes; data entry burden on field staff; marginalisation of national actors; and risk that "human oversight" becomes performative. These qualifications complicate simplistic accounts of AI as unambiguously beneficial.

Analytical insights: How AI transforms governance in conflict contexts

Beyond confirming that AI matters, the findings reveal qualitatively distinct ways in which AI transforms governance, specifically in conflict-affected humanitarian operations:

Insight 1: AI enables governance under extreme uncertainty: In conventional project management, governance assumes relatively stable environments. In North-West Nigeria, volatility is the norm. AI's predictive capabilities allow organisations to govern not by following fixed plans but by continually sensing and responding to changing conditions.

Insight 2: AI creates auditable adaptation: Donors historically struggle to fund adaptive management because adaptation looks like deviation from plans. AI tools create audit trails documenting *why* adaptations occurred, risk forecasts, supply chain analyses, and needs assessments, transforming adaptation from unapproved change to evidence-based response.

Insight 3: AI redistributes epistemic authority: AI adoption shifts whose knowledge counts. International NGOs with AI produce maps and forecasts that are treated as authoritative. National NGOs without such tools bring experiential knowledge that is systematically devalued. This redistribution has profound implications for power dynamics in humanitarian partnerships.

Insight 4: AI makes visible the invisible, and invisible the visible: AI renders certain phenomena visible: malnutrition trends across 200 villages, or patterns in security incidents. But it risks rendering other phenomena invisible: community trust, dignity in aid delivery, or the quality of human relationships. The field officer who described spending "more time looking at my phone than looking at the community" captured this paradox.

Limitations and future research

First, cross-sectional design limits causal claims. Longitudinal research tracking of organisations as they mature in AI use would strengthen evidence of causal direction. Second, self-reported data on ethically sensitive topics may be subject to social desirability bias. Future research could incorporate organisational records, donor audits, or community perspectives. Third, the focus on organisational perspectives leaves the beneficiary viewpoint unexplored. How do the affected communities experience AI-influenced governance? This is a critical gap. Fourth, AI is treated as a composite construct rather than examining specific applications. Future research could disaggregate AI types, predictive analytics, computer vision, and natural language processing, to identify which one generates which effects. Fifth, the North-West Nigeria context limits direct generalisability. Comparative studies across conflict regions could illuminate how varying dynamics shape AI integration.

7. Conclusion

This research establishes that in conflict-affected North-West Nigeria, AI tools enhance humanitarian project effectiveness by functioning as an embedded management governance infrastructure. The study's central contribution is demonstrating that AI's value is to a great extent realised through organisational readiness and ethical governance. Approximately 30% of AI tools' total effect operates through these pathways, meaning that organisations investing in AI must concurrently invest in the human and structural capabilities that enable technology to translate into improved outcomes.

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Data availability statement

The quantitative dataset analysed during this study, including survey responses from 300 participants, is available from the corresponding author, Akaninyene O. Unaam, upon reasonable written request sent to unaamakan@gmail.com. Due to the sensitive nature of the research conducted in a conflict-affected region and to protect participant confidentiality and security, the full qualitative interview transcripts cannot be shared. Anonymised excerpts of qualitative data can be made available for academic, non-commercial purposes under a signed data confidentiality agreement.

AI declaration

The authors did not use any GenAI tools in the research or in preparation of this submission.

Competing-interests declaration

The authors have no competing interests to declare.

Author contributions declaration

A. O. U.: Conceptualisation; methodology; investigation; resources; data curation; formal analysis (qualitative); writing – original draft; writing – review and editing; project administration.

E. A. U.: Methodology (quantitative instruments); software; formal analysis (quantitative); data curation; writing – original draft (quantitative sections); writing – review and editing; visualisation (tables and figures)

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Appendix A: Survey questionnaire

SECTION A: DEMOGRAPHIC AND ORGANISATIONAL INFORMATION

A1. Organisation type:
- UN Agency
- International NGO
- National NGO
- Government Agency
- Red Cross/Red Crescent Movement
- Other (please specify): ___________

A2. Your primary role:
- Senior Management (Director, Head of Office)
- Project Manager/Coordinator
- Technical Specialist (M&E, ICT, Logistics, Finance)
- Field Officer
- Advisor/Consultant
- Other (please specify): ___________

A3. Years of experience in humanitarian sector:
- Less than 2 years
- 2–5 years
- 6–10 years
- 11–15 years
- More than 15 years

A4. State of primary operation:
- Kebbi
- Katsina
- Jigawa
- Multiple states (please specify): __________

A5. Size of your organisation in the North-West region:
- Small (under 50 staff)
- Medium (50–200 staff)
- Large (over 200 staff)

A6. Primary sector of your projects (select all that apply):
- Food Security and Livelihoods
- Health and Nutrition
- Protection
- Water, Sanitation, and Hygiene (WASH)
- Shelter and Non-Food Items
- Education
- Coordination and Common Services
- Other (please specify): ___________

SECTION B: AI ADOPTION

Rating Scale:
1 = Strongly Disagree
2 = Disagree
3 = Neutral
4 = Agree
5 = Strongly Agree

	Statement	1	2	3	4	5
B1	Our organisation uses AI-powered tools for predictive risk analysis in project planning					
B2	AI applications are integrated into our project monitoring and reporting systems					
B3	We utilise machine learning or predictive analytics to anticipate supply chain disruptions					
B4	Our organisation employs AI for real-time data analysis from field operations					
B5	AI tools support our decision-making processes for resource allocation					
B6	We use automated reporting systems powered by AI for donor communication					
B7	Our organisation has invested in AI technologies specifically for humanitarian programming					
B8	Staff in my organisation regularly interact with AI-based systems in their daily work					

B9. If your organisation uses AI tools, please briefly describe the main applications (e.g., security prediction, supply chain optimisation, automated reporting, needs assessment):

SECTION C: ORGANISATIONAL READINESS

	Statement	1	2	3	4	5
C1	Our staff have adequate training to use AI tools effectively					
C2	Our organisation has the necessary technological infrastructure (internet, hardware, software) to support AI adoption					
C3	There is strong leadership support for digital and AI innovation in our projects					
C4	Our organisational culture encourages experimentation with new technologies					
C5	We have dedicated budget allocation for technology and innovation					
C6	Our organisation partners with technology providers or consultants to enhance our AI capabilities					

C7. What are the biggest barriers to AI adoption in your organisation? (Select all that apply)

- Lack of staff skills/training
- Poor internet connectivity
- Insufficient funding
- Lack of leadership support
- Staff resistance to new technology
- Ethical concerns
- Lack of appropriate software/tools
- Security concerns
- Other (please specify): ____________

SECTION D: ETHICAL GOVERNANCE

	Statement	1	2	3	4	5
D1	We have clear protocols for ethical review of AI-driven decisions					
D2	Our organisation has data protection and privacy policies that explicitly address AI systems					
D3	There are established procedures for addressing potential algorithmic bias					
D4	Beneficiary consent mechanisms are integrated into our data collection processes for AI systems					
D5	Our organisation maintains human oversight of all AI-generated recommendations					
D6	We have accountability mechanisms if AI-driven decisions cause harm					

D7. Does your organisation have a dedicated ethics committee or focal person for AI-related issues?
- Yes
- No
- In development
- Don't know

SECTION E: RISK MANAGEMENT

	Statement	1	2	3	4	5
E1	Our project risk identification processes are systematic and comprehensive					
E2	We effectively anticipate security threats to project implementation					
E3	Our organisation responds quickly to emerging risks in conflict-affected areas					
E4	Risk mitigation strategies are regularly updated based on new information					
E5	We have contingency plans that can be activated rapidly when risks materialise					

E6. In the past 12 months, how often has your organisation successfully anticipated and mitigated a major security or operational risk?
- Never
- Once
- 2–3 times
- 4–5 times
- More than 5 times

SECTION F: GOVERNANCE AND ACCOUNTABILITY

	Statement	1	2	3	4	5
F1	Our projects maintain clear documentation of all major decisions					
F2	There is transparent reporting on resource utilisation to stakeholders					
F3	Accountability mechanisms ensure responsible use of donor funds					
F4	Project governance structures include oversight from multiple organisational levels					
F5	We regularly engage with affected communities about project implementation					
F6	Decision-making processes are traceable and justifiable to external auditors					

SECTION G: TRANSPARENCY AND DONOR CONFIDENCE

	Statement	1	2	3	4	5
G1	Donors express confidence in our financial management systems					
G2	Our reporting meets or exceeds donor requirements for transparency					
G3	We proactively share project challenges as well as successes with donors					
G4	Technology has improved our ability to demonstrate accountability to stakeholders					

SECTION H: OPEN-ENDED REFLECTIONS

Please share any additional thoughts on the following questions.

- H1. In your view, what is the single biggest benefit of using AI in humanitarian project management in North-West Nigeria?
- H2. What is the single biggest risk or concern you have about AI use in this context?
- H3. Any other comments you would like to add?

Appendix B: Semi-structured interview guide

PART 1: OPENING AND CONTEXT-SETTING

Questions:

- Can you briefly describe your role and responsibilities in humanitarian programming in North-West Nigeria?
- *Probe: How long have you been in this role? What does a typical week look like?*
- How long have you worked in this region, and what do you see as the most significant challenges for project management in this conflict-affected context?
- *Probe: Security challenges? Coordination challenges? Accountability pressures?*
- [For ICT officers] What is your role in supporting technology for humanitarian operations?
- *Probe: What systems do you manage? What are the biggest tech challenges you face?*

PART 2: AI APPLICATIONS AND EXPERIENCES

Questions:

- Is your organisation currently using any AI or advanced analytics tools in project management? If yes, please describe:
- What specific tools or applications?
- What functions do they perform? (e.g., risk prediction, monitoring, reporting, needs assessment)
- How long have these tools been in use?
- *Probe: Can you show me an example or walk me through how it works?*
- [If not using AI] Has your organisation considered adopting AI tools? What factors have influenced this decision?
- *Probe: What would need to change for you to consider adoption?*
- Can you share a specific example where AI tools influenced a project management decision? What happened, and what was the outcome?
- *Probe: Walk me through that situation step by step. What information did the AI provide? What did you do with that information?*
- In your experience, how do AI tools compare to traditional approaches for:
- Risk identification and mitigation?
- Resource allocation?
- Monitoring and evaluation?
- Donor reporting?
- *Probe: What does AI do better? What do traditional approaches do better?*

PART 3: GOVERNANCE AND DECISION-MAKING

Questions:

- How do AI-generated insights or recommendations factor into your project governance processes?
- Are they advisory or determinative?
- Who reviews AI outputs before action is taken?
- *Probe: Is there a formal process for this?*
- What role does human judgment play alongside AI tools in your organisation? Can you describe a situation where human judgment overrode an AI recommendation?
- *Probe: What happened? Why did the human override? What was learned?*
- How have AI tools affected accountability relationships:
- With donors?
- With affected communities?
- Within your organisation?
- *Probe: Has accountability improved? Have new accountability challenges emerged?*

- What governance mechanisms does your organisation have in place to oversee AI use? (e.g., ethics committees, review protocols, oversight boards)
- *Probe: Are these formal or informal? How well do they work?*

PART 4: ORGANISATIONAL READINESS AND CONSTRAINTS

Questions:

- How would you assess your organisation's readiness for AI adoption in terms of:
- Staff skills and training?
- Technological infrastructure (internet, hardware, software)?
- Leadership support?
- Financial resources?
- *Probe: What is the biggest gap?*
- What have been the biggest challenges in implementing or using AI tools in this context?
- Infrastructure challenges?
- Skills/capacity challenges?
- Cost/funding challenges?
- Cultural resistance?
- Ethical concerns?
- Probe: Which challenge has been most difficult to overcome?
- What has enabled or facilitated AI adoption where it has been successful?
- *Probe: Was it leadership? Donor requirements? Partnerships? Staff champions?*
- How do you see the digital divide, between international and national NGOs, or between urban and field operations, affecting AI adoption in humanitarian work?
- *Probe: Are some actors being left behind? What are the consequences?*

PART 5: ETHICS, RISKS, AND SAFEGUARDS

Questions:

- What ethical concerns or risks related to AI use in humanitarian contexts concern you most?
- Data privacy and protection?
- Algorithmic bias or discrimination?
- Exclusion of vulnerable groups?
- Accountability gaps when things go wrong?
- Surveillance or misuse of data?
- *Probe: Which keeps you up at night?*
- How does your organisation address these concerns?
- What policies or practices are in place?
- Are these adequate, in your view?
- *Probe: Can you give me an example of a time these safeguards were used?*
- Have you encountered any unintended consequences of using AI in humanitarian operations? Please describe.
- *Probe: Something that surprised you, positive or negative?*
- How do you balance the efficiency gains from AI against potential risks to beneficiaries or staff?
- *Probe: Is there a tension? How do you navigate it?*

PART 6: FUTURE DIRECTIONS AND RECOMMENDATIONS

Questions:

- Looking ahead, how do you see AI evolving in humanitarian project management in North-West Nigeria over the next 3–5 years?
- *Probe: What will change? What will stay the same?*
- What recommendations would you offer to:
- Humanitarian organisations considering AI adoption?
- Donors funding technology in humanitarian contexts?
- Policymakers or regulators?
- *Probe: What do you wish someone had told you when you started?*
- If you could design the ideal AI tool for humanitarian work in this context, what would it do?
- *Probe: What problem would it solve?*
- Is there anything else you'd like to share about AI and humanitarian governance that we haven't discussed?
- *Probe: Any final thoughts, concerns, or hopes?*