International Journal of Scientific Research and Modern Technology (IJSRMT) ijsrmt.com
Volume 3, Issue 8, 2024
DOI:https://doi.org/10.38124/ijsrmt.v3i8.896

AI-Driven Systems for Predicting Zoonotic Disease Outbreaks in Rural Livestock Communities: A Questionnaire-Based Descriptive Study

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Publishing Date: 2024/08/28

Abstract

This study seeks to understand the readiness, perceptions, and resource capacities of livestock owners and veterinary personnel toward the use of AI-powered systems to anticipate zoonotic disease outbreaks in rural livestock communities. It involved the distribution of a structured questionnaire to 200 individuals in the rural livestock community, with a descriptive statistical approach (frequency, percentage) being employed to summarize the data. Notably, 72% of respondents understand the value of AI systems, but only 24% think the community has the requisite supportive infrastructure. Response distributions for the various domains (awareness, infrastructure, willingness, constraints) are summarized in the tables and accompanying narratives of interpretation. These chapters relate to the literature on the use of AI in zoonotic disease surveillance, and the absence of literature on the gaps of trust, integration, and capacity for evidence-based surveillance. AI systems for surveillance in resource-poor settings will require significant training, infrastructure development, and revised policies. Other major stakeholder recommendations include deployment in phases, training, and development of regulatory policies.

Keywords: *AI, Zoonotic Disease Prediction, Rural Livestock, Questionnaire Survey, Descriptive Analysis, Surveillance.*

I. INTRODUCTION

Zoonotic diseases, a diseases that transfer between animals and humans remain a universal threat to both public health and livestock effectiveness (Abdulrazaq et,al., 2024). Almost 70 percent of emerging and infectious diseases are animal borne. This puts rural livestock communities at the center of the risk of zoonotic spillover. After animals, the next likely source of infectious disease risk is rural livestock communities. AI is now expected to be able to predict disease emergence, because it can analyze different patterns of risk data environmental, biological and socio-behavioral (Tshimula, et.al., 2024). So far, most of the AI modeling has been done in data-rich communities, and the use of AI in rural resource-poor livestock communities is still a blank canvas.

This study attempts to document the gap by using surveys and descriptive analysis to understand the rural livestock stakeholders' readiness, perceptions, and constraints in utilizing AI for predicting zoonotic diseases. Specifically, the objectives are to: (i) understand the awareness and perceptions of stakeholders; (ii) identify the infrastructure and institutional bottlenecks; (iii) assess stakeholder willingness; and (iv) outline evidence-based recommendations.

The rest of the document will unfold as follows: First, a review of the literature will be provided in Section 2. Section 3 will explain the methodology. The results will flow from Section 4, which contains the tables and a detailed explanation of the findings. In Section 5, the discussion will integrate the results with the literature. The last Section, 6, will provide the conclusion, followed by Section 7, which will provide the recommendations. The last section will be the references.

II. LITERATURE REVIEW

- *AI in Predicting Zoonotic Diseases*

Artificial intelligence, notably machine learning (ML) and deep learning techniques, has been employed in predicting zoonotic diseases, identifying risk factors, and formulating strategies to mitigate its effects. Towfek & Elkanzi (2024) provides a systematic and comprehensive review of machine learning techniques including random forest, support vector machines, and neural networks that predicted zoonotic disease outbreaks and identified key drivers.

A notable illustrative example involves using AI and big data to predict the risk of vector-borne diseases by constructing early warning systems that use environmental (e.g. rainfall, temperature) and host density. Guitián et al. makes a similar argument that ML in agricultural systems can provide real-time risk prediction by integrating surveillance and diverse prediction variables.

➢ *Applications in Livestock and Veterinary Settings*

AI is being evaluated in veterinary medicine and animal health for its potential in detecting subclinical conditions, optimizing treatment, and conducting syndromic surveillance. Alzubi (2024) argues that AI could analyze times series and spatial health metrics like milk production, reproduction, and mortality rates, which could lead to detecting infections much early at the individual or herd level.

On the livestock disease front, a more recent work on ML frameworks for disease management in cattle used Naive Bayes, support vector machines, and decision tree classifiers to analyze sensor and health record data to detect cattle disease patterns. The authors claim the proposed ML systems will enhance the accuracy of detecting livestock diseases and automate the decision support systems for livestock producers. While the studies mentioned have made significant contributions to the advancement of the sector, they overlook the reality of rural low resource settings where sensor systems, diagnostic tools, and computational power are lacking, and where a large volume of data is not.

III. METHODOLOGY

➢ *Research Design*

This is a cross-sectional descriptive study using a structured questionnaire administered to livestock farmers, veterinary personnel, and community leaders in rural livestock communities.

➢ *Sampling and Respondents*

For this research, 200 respondents were purposively sampled from (specify region, e.g. Oyo State, Nigeria). Respondents included 150 livestock keepers, 30 veterinary extension officers, and 20 community leaders.

➢ *Instrument*

The questionnaire consists of the following sections:

- Demographics: age, education, types of livestock, herd size
- Awareness of and perceptions toward AI-based disease prediction
- Infrastructure and resource readiness (electricity, internet, devices)
- Willingness and intention to adopt AI systems
- Constraints and barriers perceived

The response formats included a combination of binary, Likert-scale (e.g. strongly disagree to strongly agree), and multiple-choice questions. The questionnaire was pretested among 20 respondents from a neighboring community and minor revisions were made to enhance clarity.

➢ *Data Collection*

In rural communities, trained enumerators conducted in-person administration of the questionnaires over the course of two weeks.

➢ *Data Analysis*

The analysis is predominantly descriptive. Responses are displayed and summarized in frequency and percentage tables. Each table is supplemented with a detailed written analysis, highlighting pertinent trends, outliers, and stakeholder groups.

Since the emphasis is on perceptions and preparedness rather than causation, there is no use of inferential statistics or causal modeling such as regression.

➢ *Ethical considerations*

All participants consented, either verbally or in writing, and confidentiality was preserved by anonymizing records. Ethical clearance was sought from the relevant institutional review board

IV. FINDINGS

Table 1 Awareness and Perceptions of AI-Based Prediction (n = 200)

Statement	Frequency (Agree / Yes)	Percentage (%)	Frequency (Disagree / No)	Percentage (%)
I have heard of AI-Driven Disease Prediction	144	72.0%	56	28.0%
I believe AI Systems can help prevent Disease Outbreaks	130	65.0%	70	35.0%
I trust AI Predictions in Livestock Health	90	45.0%	110	55.0%
I think Community will Accept AI Tools	120	60.0%	80	40.0%

- *Awareness:*

72% (144/200) of respondents report having heard of AI-driven disease prediction, which is relatively high for a rural livestock context. This suggests some level of exposure to the concept of AI, perhaps through media, extension outreach, or word-of-mouth. Belief in utility: 65% (130/200) believe AI systems can help prevent disease outbreaks. This indicates moderate optimism about the potential of AI among stakeholders.

- *Trust in Predictions:*

Only 45% (90/200) express trust in AI predictions, while 55% (110/200) do not. This split suggests significant skepticism, likely due to unfamiliarity, perceived opacity of AI models, or fear of incorrect predictions.

- *Community Acceptability:*

60% (120/200) feel their community would accept AI tools. This is encouraging, though the 40% dissent shows that acceptability is not universal—and social or cultural resistance may be a barrier. Overall, while awareness and belief in potential are reasonably strong, trust and full acceptability lag behind, pointing to the need for trust-building, transparency, and demonstration of performance.

Table 2 Infrastructure and Resource Readiness (n = 200)

Resource / Condition	**Frequency (Available)**	**Percentage (%)**	**Frequency (Not Available)**	**Percentage (%)**
Reliable Electricity	80	40.0%	120	60.0%
Internet Connectivity	50	25.0%	150	75.0%
Smartphone or Computer Ownership	100	50.0%	100	50.0%
Access to Technical Support	60	30.0%	140	70.0%

- *Electricity:*

A portion of the population, specifically 40%, indicate the supply of reliable electricity while 60% report unreliable supply or no electricity supply, ultimately indicating major infrastructural gaps. This becomes extremely important when considering the infrastructural challenges posed by AI systems, edge systems, or edge computing technologies, which primarily rely on uninterrupted power supply. Internet: Only 25% of the population report having internet connectivity, while a shocking 75% report not having internet, under these circumstances, weak connectivity negates the possibility of cloud-based AI applications or remote updates, forcing dependence on offline solutions.

- *Device Ownership:*

Half of the population (i.e. 50%, or 100/200 people) own a smartphone or computer which is quite modest. For AI adoption, those devices must be owned by a significant user base or extension personnel.

- *Technical Support:*

A very tiny number, specifically 30%, report having access to technical support or maintenance services, indicating that unsanctioned adoption is self-defeating, meaning unsupervised AI systems will ultimately fail. Here, the lack of infrastructure practically confirms that these people have no room to adopt AI systems. Addressing the issues of electricity, connectivity, devices, and support is no doubt a prerequisite.

Table 3 Willingness and Intention to Adopt AI Systems (n = 200)

Statement	**Frequency (Agree / Yes)**	**Percentage (%)**	**Frequency (Disagree / No)**	**Percentage (%)**
I would use an AI Tool if Available	110	55.0%	90	45.0%
I would pay for AI-Based Advisory Services	70	35.0%	130	65.0%
I prefer Gradual Integration (hybrid) Over full Automation	140	70.0%	60	30.0%
I would Participate in Training on AI Use	150	75.0%	50	25.0%

About half of respondents are willing to adopt AI tools. While 55% (110/200) are willing to use an AI tool if available, 45% (90/200) are not. This indicates slight willingness to adopt an AI tool, yet, close to half are willing to use AI tools if available. Answering the question of willingness to pay, only 35% (70/200) are willing to pay for AI-based advisory services. This indicates that most likely, AI advisory services will be expected to be for free. There is a big, 70% (140/200) majority which would prefer a gradual hybrid integration (i.e. both AI and a human would oversee the process) instead of complete automation. This is likely due to the need to keep human control of the process and the need for integration not to be complete a sudden shift of control. There would be no sudden control of the process. In summary, the majority are willing to adopt AI tools, although the willingness is not backed by financial investment, and the caution displayed is indicative of a preference for an incremental approach. The willingness for training, however, is a good sign.

Table 4 Perceived Constraints and Barriers (n = 200)

Barrier	Frequency (Yes)	Percentage (%)
Lack of funds to procure equipment	160	80.0%
Skepticism or mistrust	120	60.0%
Poor network/internet	150	75.0%
Lack of trained personnel	140	70.0%
Maintenance and support challenges	130	65.0%
Fear of job displacement	70	35.0%

Financial constraint: 80% (160/200) cite lack of funds as a barrier. This is the most frequently mentioned constraint and reflects economic realities in rural areas. Skepticism/mistrust: 60% (120/200) express skepticism or mistrust in AI. This confirms the trust gap noted earlier. Poor network: 75% (150/200) name poor network/internet connectivity as a barrier, aligning with earlier infrastructure findings. Lack of trained personnel: 70% (140/200) see absence of trained staff as a hurdle, echoing the need for human capacity building. Maintenance and support: 65% (130/200) anticipate challenges in maintenance and technical support—underscoring sustainability concerns. Fear of job displacement: 35% (70/200) worry that AI may displace roles (e.g. veterinary advice), although this is less frequently cited. Taken together, the barriers suggest that the pathway to adoption will need to overcome financial, infrastructural, capacity and trust bottlenecks.

V. DISCUSSION

Some people reported reasonably high levels of awareness (72%) toward advances in AI-based disease prediction but only 45% expressed trust in the prediction. This disparity has been highlighted in the literature, especially when new technology like AI comes in. Building trust seems achievable using tools such as pilot projects, explanations of model workings (predictive modeling), and human-in-the-loop systems. As the literature describes the phenomenon of AI predicting technology, the human incremental adaptation systems will likely describe the integration systems as the remaining systems as AI predicts levels of overshoot and relies fully on AI. The expected infrastructural resiliency in the communities within the study seems weak, as only 40% of the communities have steady access to electricity, 25% to the internet, 50% to internet-enabled devices, and 30% offer any kind of technical assistance. These patterns echo the literature which describes the disparity in AI systems serving rural area vs capitalized areas presupposed layers of data, connectivity, and computation. In the case of addressing rural areas, foundational layers of any AI system will encounter incredible constraints.

The modest willingness to undergo training (75%) seems to indicate latent potential. This training is only constructive when the infrastructure is available and there is any structured use of AI technology, which in most rural areas is practically non-existent, as provided AI systems are still poorly designed. Non-availability of paying for the system seems to be a major barrier as only 35% reported willingness to pay for AI advisory services. Hence, it is suggested that there should be models that are subsidized and models that are pivate public partnerships as purely market driven approaches would fail. This is the same as findings in other divisions where innovations in AI do not scale simply due to lack of funds. Mistrust and skepticism (60%), lack of trained personnel (70%), and maintenance issues (65%) demonstrate the weaknesses in the systems. AI adoption is influenced positively by the literature on governance, regulatory building, data sharing, and coordination of affected and interested parties. Regarding rural livestock, these extension staff, veterinary service providers, and local government agencies must work together to promote integration.

VI. CONCLUSION

This study has examined the perceptions, the levels of readiness, and the barriers stakeholders face around AI powered systems designed to predict zoonotic disease outbreaks in rural livestock communities. The awareness and optimism in the community is clear, but the gaps that lie in trust, infrastructure, finances, and human resources are quite stark. These must be attended to if AI systems are to be put in these environments. AI has the potential to provide rural livestock communities with the early warning of zoonotic diseases, but the sophisticated models will not deliver unless the underpinning structur will provide the necessary electricity, connectivity, trust, skills, and institutional framework.

RECOMMENDATIONS

Based on findings and literature, the following recommendations are made:

- Pilot Demonstration Projects: Initiate small-scale pilot projects in target communities with interested participants as a means to demonstrate value and gain confidence.
- Hybrid Human-AI Workflow: Use systems that support, rather than take over, human decision making systems to allow gradual acclimatization.
- Capacity Building and Training: Design training materials (in the local language) for farmers, extension agents, and veterinarians on how to use and analyze the results of the AI systems.
- Infrastructure Investment: Work with the government and NGOs to improve and expand access to electricity, the internet, and devices in rural areas.
- Subsidy or Incentive Models: Implement subsidies, grants, and approved cost-sharing programs to diminish the financial obstacles for the use of AI advisory services.

- Stakeholder Engagement and Trust Building: Use participatory design with community leaders, farmers, and veterinarians to cultivate a sense of ownership and promote the idea of transparency and acceptability.
- Policy and Governance Frameworks: Establish the necessary regulatory and institutional frameworks for the governance of data sharing and control, privacy, model validation, and the overall sustainability of AI in agriculture and animal health.
- Continuous Monitoring and Feedback: Design systems to oversee performance and capture insights to improve AI systems.
- Future research may expand upon this descriptive work by deploying actual AI prototypes in rural settings, evaluating model performance, and conducting longitudinal studies to measure impact on disease outbreaks and livestock health.

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