Engineering and Technology Journal e-ISSN: 2456-3358
Volume 11 Issue 04 April-2026, Page No.-9454-9461
DOI: 10.47191/etj/v11i04.15, I.F. – 8.595

Artificial Intelligence Techniques in Enhancing Livestock Adaptation to Climate Change: A Systematic Literature Review

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ABSTRACT: Climate change is increasingly affecting livestock systems worldwide by exacerbating heat stress, water shortages, and disease prevalence, which are critical challenges that can jeopardize the productivity and sustainability of this sector, particularly in vulnerable areas. In this context, this research aims to conduct a systematic literature review of 60 reviewed articles to examine the contribution of artificial intelligence (AI) in enhancing the adaptation of the livestock sector to climate change. The literature review has synthesized the major opportunity domains, factors of adoption, barriers to adoption, areas of application, and theory base. The research has found that AI is mainly used in heat stress detection, disease monitoring, and productivity optimization. However, its adoption is significantly influenced by technological and economic feasibility. On the other hand, the major barriers to adopting AI are high implementation costs and lack of infrastructure. A critical gap in research is that most literature has not adopted a comprehensive theory base to explain the complex factors affecting AI adoption in the livestock sector. To this end, a new conceptual framework is introduced that incorporates AI attributes, climate stressors, adaptation mechanisms, production results, and adoption factors. This framework is envisioned to serve as a holistic window for forthcoming studies and practice, recognizing that successful AI implementation is not only about technological advancements but also about facilitating infrastructure, capacity development, and policy support. This paper makes a theoretical and practical contribution to the field by synthesizing information in an organized manner and informing future studies that can deliver a more comprehensive AI-driven solution.

KEYWORDS: Artificial Intelligence, Livestock Systems, Climate Change Adaptation, Precision Livestock Farming, Climate Resilience

I. INTRODUCTION

However, the changing climatic conditions are posing a rising threat to food security and the sustainability of pastoral and farming systems in low- and middle-income countries. This is indicated by the rising levels of heat stress, scarcity of feed and water, and the incidence of diseases in livestock systems [1-3]. In the recent reviews on the subject, it is emphasized that innovations in data-driven approaches such as precision livestock farming (PLF), sensor systems, and data analysis are becoming vital in building the resiliency of livestock systems in the face of rising climatic variability. In the field of climatic resiliency, the sector of agriculture and food systems is the most dynamic platform for implementing AI-driven resiliency innovations, thus underlining the importance of AI in building the resiliency of livestock systems.

In the context of livestock development, AI has been incorporated in the form of PLF technologies, where computer vision, wearable technology, and decision support through machine learning are combined to optimize feeding patterns, diagnose diseases at early stages, control reproduction cycles, and monitor welfare. This has been done to enhance productivity and sustainability in the face of climatic stressors [7]. Technologies based on deep learning and IoT are being used to monitor the health, behavior, and stress conditions of animals, thereby paving the way for personalized management in extreme environments [4, 8]. Moreover, genomic and landscape studies are now being done with the help of AI to associate the genetic characteristics of animals with environmental characteristics and climate patterns, thereby aiming to enhance the intrinsic heat and stress tolerance in animals [9].

Despite its promise, the deployment of AI in livestock production, especially in developing countries, is uneven. Its implementation is hampered by a variety of socioeconomic, infrastructural, and institutional challenges. Systematic reviews of literature revealed that the major challenges associated with AI in livestock production are related to cost, connectivity, data management, and farmer concerns about complexity, trust, and data ownership, among others [10, 11]. Similarly, technology adoption research that employed models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) revealed that factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions significantly influenced AI and IoT adoption in agriculture. Extension support and policy issues are also challenges that hamper AI adoption in agriculture, especially by smallholder farmers. In this context, this study employed a systematic literature review (SLR) to find answers to the research questions:

1. How is artificial intelligence (AI) currently used in livestock production in the climate change era?
2. How are AI techniques utilized to enhance livestock adaptation and resilience to climate change?
3. Why is it challenging to adopt AI technologies for livestock adaptation in developing regions?
4. What factors influence the adoption of AI-driven livestock adaptation practices?

Through the synthesis of existing evidence, this review seeks to develop an extensive understanding of the status quo in AI in livestock adaptation, as well as identify key gaps and create a roadmap for future research and practice.

II. METHODOLOGY

This study utilized a systematic literature review using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol. This process consists of four major steps: the literature search, the screening process, the eligibility assessment, and the inclusion process.

The literature search involved using various online databases such as PubMed, Springer Link, Science Direct, ACM, and IEEE Xplore to obtain a comprehensive and representative number of studies published between 2021 and 2025. Since there is a limitation in using the Boolean operator in Science Direct, two search strings are utilized in the process:

General Search String: ("artificial intelligence" OR "AI" OR "machine learning" OR "ML" OR "deep learning" OR "DL" OR "precision livestock farming") AND (livestock production OR "animal production" OR "cattle production" OR "dairy production") AND ("climate change" OR "climate resilience" OR "climate adaptation").

ScienceDirect Search Stringy ("artificial intelligence" OR "machine learning" OR "precision livestock farming") AND (livestock OR "animal production" OR cattle) AND ("climate change" OR "climate resilience" OR "climate adaptation")

Inclusion criteria for the study included peer-reviewed articles and conference proceedings published in English, within a range of 2021 to 2025, and focused on applying AI in livestock production for addressing issues of climate change, resilience, or stressors. Systematic literature reviews, grey literature, editorials, and articles without a clear connection to AI in livestock production for adapting to climate change were excluded.

The search yielded a total of 4,344 articles. From this, 6 duplicate articles were removed, and 4,235 articles were excluded based on title and relevance to the research objectives. Then, 103 articles were subjected to abstract screening, resulting in the exclusion of 24 articles. Finally, a further 6 articles and 13 systematic literature reviews were excluded after a detailed reading of the articles. A total of 60 articles were included for further in-depth study. Figure 1 presents a flow diagram of the selection process, based on the PRISMA flow chart.

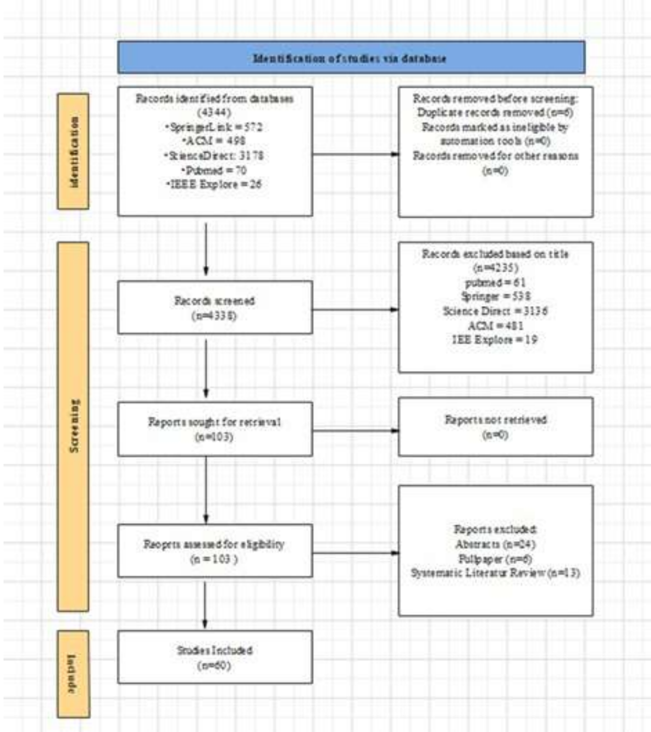

Figure 1: PRISMA Flow Diagram

III.RESULTS

The 60 selected studies were analysed for publication trends, geographic distribution, methodologies, and theoretical frameworks

A. Publications per Year

From the temporal analysis, it is evident that there is an increasing trend in research output over time. The research output has risen from 7 papers in 2021 to 22 papers in 2025. This indicates an increasing interest in research regarding the application of AI for livestock climate adaptation (Table I). The highest output in 2025 indicates maturity in the domain.

Table I: Distribution of Publications per Year (n=60)

Year	Count
2021	7
2022	9
2023	13
2024	7
2025	2
2026	2

B. Geographic Distribution of Publications)

The geographic distribution analysis demonstrates a wide disparity in the research output. Europe is the leader in this context, with 31 research studies, followed by Asia (16), Africa (7), North America (4), South America (1), and Oceania (1). The high number of research studies in the European region demonstrates the high investment in PLF and digital infrastructure, whereas the low number of research studies in Africa emphasizes the research gap in this region, which is very vulnerable to climate change. Table 2 categorizes studies by context.

Table 2: Distribution of Publications per Year (n=60)

Context	Count
Asia	16
Africa	7
North America	4
South America	1
Oceania	1
Unspecified	29

C. AI Applications in Livestock Production

The literature review identified several key application areas where AI is being used in livestock systems, as presented in Table II. Heat stress detection and management comprise the most studies, at 30, followed by disease detection and health monitoring, with 22 studies. Figure 2 depicts the literature-based applications of AI in livestock management.

Figure 2: AI Application areas in Livestock Management

This is supported by existing literature, which indicates that AI is being used in livestock farming to mitigate the effects of climate-induced stressors. Precision livestock farming, which incorporates IoT devices and machine learning algorithms, is the main AI paradigm used in livestock farming. This is due to its ability to monitor animal health, behaviour, and environmental conditions in real time [70, 71]. Other AI applications, such as computer vision for heat stress detection and disease surveillance through wearable sensors, are well-established, especially in dairy and poultry farming in developed countries [72, 73]. In addition, AI is being used in predictive analytics to forecast losses in production, disease outbreaks, and management interventions. This is expected to shift the focus from reactive adaptation to anticipatory adaptation. Genomic selection is another emerging long-term adaptation strategy in which AI is being used to breed animals with desirable traits such as thermotolerance and drought resistance.

The AI tools applied for the areas in Figure 2 include Sensor-based monitoring, ML prediction models, wearable sensors, Predictive feeding strategies, efficiency models, Integrated environmental and predictive modelling systems, AI-driven genomic and resilience-based breeding, etc. However, despite the proven potential, the adoption of AI technologies in developing countries faces numerous challenging factors.

D. Factors Influencing the Application of AI in Livestock Management

The process of synthesis indicates an intricate relationship of factors affecting AI adoption (Table 3). The main opportunities relate to building climate resilience (28 studies) and promoting productivity (26 studies). On the other hand, the main challenges relate to high implementation costs (38 studies) and poor digital infrastructure (32 studies), followed by limited technical knowledge (30 studies).

Table 3: AI Application Factors

Factor	Count
Technological Readiness	32
High Implementation Cost	38
Economic Feasibility	30
| Poor Digital Infrastructure	32
Human Capacity & Digital Literacy	28
Institutional & Policy Support	22
Data-Related Challenges	24
Data Availability & Quality	20
| Institutional & Policy Constraints	18

This is in line with the results obtained in our barrier analysis. The high cost of sensors and digital infrastructure is one of the most important barriers for smallholder systems [76]. This is exacerbated by the low digital infrastructure in developing countries, such as the reliability of electricity and the internet [76], which makes the implementation of most AI technologies impossible. In addition, the low digital literacy of farmers and the absence of extension services are important barriers [79]. The above-mentioned results clearly indicate that it is impossible to implement technologies in a vacuum.

Another significant finding of the review is that there is a lack of studies that use strong theoretical frameworks to explain the process of adoption. Most of the studies only concentrate on the technical performance of the models, such as accuracy, without considering other factors that affect the process of adoption in real-world scenarios. The use of TAM and COM-B theories is sporadic and indicates that the usefulness and ease of use of the system, as perceived by the user, and the capacity of the user to use the system, respectively, are essential factors in the process of adoption, as suggested in [17, 41]. However, the absence of an integrated theory that considers other factors, such as infrastructure and economics, is a major limitation of the current body of knowledge in the area of AI adoption. As suggested in [80], the use of participatory approaches in which the local community is involved in the process of design and implementation is crucial in ensuring the success of AI systems in real-world scenarios.

E. A Conceptual Framework for AI-Enabled Livestock Production in the Era of Climate Chance

To address the identified gaps, we develop a new conceptual framework that integrates the results of this review (see Figure 3). This framework is expected to inform future empirical studies and practices by taking a comprehensive approach to understanding the multifaceted nature of AI adoption for climate adaptation.

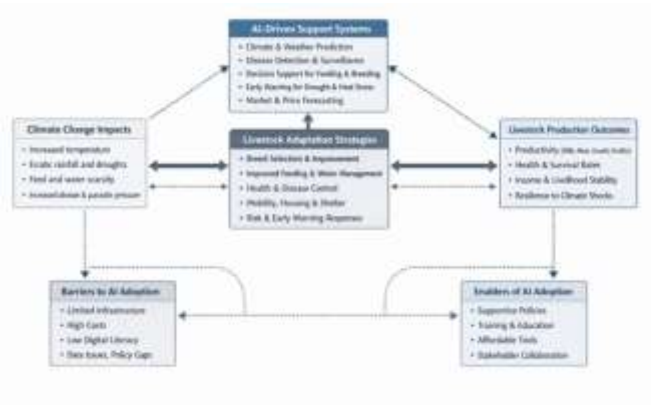

Figure 3: A Conceptual Framework of AI in Livestock Management

The framework is developed on the basis of five key constructs, which are interconnected with each other:

1. .AI Capabilities: These include the technological components of the framework, such as machine learning, IoT, computer vision, genomic analytics, etc., which provide data-driven insights.
2. Climate Stressors: These include the environmental challenges, such as heat stress, drought, water scarcity, disease, etc., which affect livestock.
3. Livestock Adaptation Strategies: These include the various management strategies, such as heat abatement, precision feeding, breeding, disease control, etc., which are used to combat the effects of climate stressors.
4. Livestock Production Outcomes: These include the various measurable outcomes of adaptation, such as improved productivity, health, survival, etc.
5. Adoption Determinants: These are the key factors which mediate the association between AI capabilities and adaptation, including:

-Technological & Economic: These factors include infrastructure, cost, data, etc.

-Human & Social: These factors include human factors, such as human skills, trust, etc.

-Institutional & Policy These factors include government support, extension services, policies, etc.

The framework suggests that Climate Stressors give rise to Adaptation Strategies, which can be improved by AI Capabilities. The effectiveness of such an improvement is subject to Adoption Determinants. Adaptation Strategies, in turn, lead to better Production Outcomes. Feedback loops are also included in the framework, which allow for the refinement of AI models based on the outcome, as well as the development of policies through the experience of stakeholders.

V. CONCLUSIONS

This systematic review of existing literature also verifies the potential of artificial intelligence in revolutionizing the adaptation of livestock to changing climates. There are definite prospects of enhancing such adaptation through AI-based solutions in detecting heat stress, disease monitoring, and genomic selection. However, it is also evident that despite such definite prospects, there is a wide gap between potential and actualization, especially in developing countries.

The most notable gap in existing research is the absence of an integrated theoretical framework in understanding and implementing AI in this context. Most of the existing research is highly technical in nature and does not take into consideration the various complexities of success in adoption. In order to bridge this gap, it is proposed in this paper to develop an overall conceptual framework that incorporates the capabilities of AI with its implications in adapting to changing climates, production outputs, and various determinants of adoption.

Through embracing such a systemic approach, it is hoped that future research will be able to go beyond isolated technical assessments in order to produce more relevant findings for policy-makers, practitioners, and technology developers. This will be crucial in order to ensure that the potential of AI is harnessed in an equitable manner in order to not only ensure survival but thrive in an era of climate change.

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