ORIGINAL ARTICLE

Applications of Artificial Intelligence in Malaria Vector Control in East Africa: A Scoping Review of Existing Evidence, Challenges, and Future Prospects

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ABSTRACT

Background: Malaria remains a leading cause of morbidity and mortality in East Africa despite decades of control efforts. Interventions such as long-lasting insecticidal nets (LLINs), indoor residual spraying (IRS), and larval source management have reduced transmission, yet progress is threatened by insecticide resistance, climate variability, and evolving mosquito behaviour.

Objective: This scoping review explores the application of artificial intelligence (AI) malaria vector control across East Africa. It aims to synthesize existing evidence, identify challenges, and inform future research and policy directions.

Methods: A comprehensive literature search was conducted using electronic databases and grey literature sources, following the PRISMA for Scoping Review guidelines. PubMed, Google Scholar, Science Direct and IEEE Xplore were databases used to search for scientific evidence. Studies were included if they addressed artificial intelligence applications in malaria surveillance, prediction, or intervention optimization within East African contexts. Data were charted synthesised across key thematic domains.

Results: Six scientific studies met the inclusion criteria for this scoping review. Evidence suggests growing interest in the use of artificial intelligence for vector habitat mapping, transmission risk forecasting, and malaria vector identification and surveillance. While these approaches show promise in enhancing malaria control, challenges persist, including limited data quality, algorithmic bias, and weak integration into national malaria programs.

Conclusion: Artificial intelligence offers significant potential to strengthen malaria vector control in East Africa by supporting data-driven, targeted interventions particularly through improved prediction, surveillance, and decision-making tools. However, their implementation remains limited, with notable regional gaps and operational challenges. Future work should focus on translating existing innovations into field-ready tools, expanding research across underrepresented countries, and fostering cross-sector collaboration to ensure AI contributes meaningfully to malaria vector control with elimination goals.

BACKGROUND

Malaria remains one of the most pervasive and deadly infectious diseases worldwide, with Sub-Saharan Africa bearing the greatest burden. According to the World Health Organization (WHO), an estimated 2.2 billion cases of malaria and 12.7 million deaths have been averted since 2000, but the disease remains a serious global health threat, particularly in the WHO African Region. [1] Malaria remains a persistent public health challenge in East Africa, where high transmission intensity continues to drive substantial morbidity and mortality. Over the past few decades, substantial malaria vector control efforts have been made to reduce malaria transmission and mortality. Strategies like long lasting insecticide treated net (LLINs) and indoor residual spraying (IRS), have proven effective in many areas. However, despite these gains, the fight against malaria faces several formidable challenges. The rise of insecticide resistance is one of the most pressing issues.[4–8] The effectiveness of both ITNs and IRS has been severely compromised by the development of resistance in mosquito populations to the insecticides commonly used in these interventions.[9,10] This resistance, coupled with the behavioural adaptations of mosquitoes, such as early biting and exophilic tendencies (biting outdoors), [11,12] has made controlling the mosquito vector more difficult. In addition, changes in climate, human migration patterns, and land use (factors that influence mosquito habitats) further complicate efforts to predict and manage malaria transmission.[13,14]

In recent years, artificial intelligence (AI) and machine learning (ML) have emerged as promising tools for enhancing malaria vector control. These technologies offer potential for improved prediction, more efficient surveillance, and optimized targeting of interventions by leveraging large, heterogeneous data sources and enabling real-time decision-making, [15] For instance, AI-driven models can analyse climate variables, larval habitat maps, and insecticide resistance patterns to forecast malaria risk and guide control efforts. [16] However, despite these advances, the extent to which AI has been systematically applied, evaluated, or integrated into malaria control programs across East Africa remains inadequately explored. This highlights the urgent need for a comprehensive review to map existing applications, identify challenges to implementation, and inform future research and policy directions.

This scoping review aims to map the current evidence of AI applications in malaria vector control across East African countries, focusing on three key domains: scientific evidence methods on AI tool used particularly predictive modelling and machine learning, and challenges alongside future prospects. By systematically summarizing methodologies, findings, and gaps, this review seeks to clarify AI's role in strengthening malaria control and guide strategies for more effective and equitable implementation in the region.

METHODS

Definition of Artificial Intelligence

Artificial intelligence has varying definitions tailored to specific context. For the context of this scoping review, AI is defined as the use of algorithms. The term "algorithms" refers to specific instructions for solving a problem or performing a calculation. [16] Therefore, this scoping review will assess studies that adhere to the definition including machine learning and predictive modeling.

Review Framework

The review is reported in accordance with the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) guidelines.[17]

Geographic Scope and Country Selection

This scoping review focuses on five East African countries: Kenya, Uganda, Tanzania, Rwanda, and Burundi. These countries were selected based on the following rationale:

- High Malaria Burden – All five countries experience substantial malaria transmission and are prioritized by the World Health Organization (WHO) for intensified malaria control. [1]
- Shared Epidemiological and Ecological Features – The region exhibits similar malaria vector species, transmission dynamics, and environmental conditions, allowing for meaningful comparative analysis of AI applications. [18–21]
- Comparable Health System Constraints – These countries face common operational challenges in malaria control, including limited entomological data, constrained financial and human resources, and variable access to health technologies. [18–21]
- Regional Integration and Policy Alignment – As members of the East African Community (EAC), these countries collaborate on cross-border malaria control efforts, share research platforms, and align their policy initiatives. [22]

In light of these factors, this review aims to map the current evidence of AI applications in malaria vector control across these five countries, identify key implementation challenges, and highlight opportunities for future research and policy action.

Research Questions

1. How has AI been applied to improve data collection in malaria vector control studies, particularly in integrating diverse data sources such as surveillance, insecticide resistance, habitat mapping, and vector control interventions in Kenya, Tanzania, Uganda, Rwanda, and Burundi?
2. In what ways have AI techniques been used to enhance data analysis within malaria vector control frameworks, including predictive modelling and risk factor estimation?
3. How have AI contributed to efficiency or predictive accuracy in malaria vector control in East Africa?
4. What are the reported challenges and recommendations associated with implementing AI in malaria vector control in East Africa?
5. What are the future prospects for integrating AI into malaria vector control in East Africa?

Eligibility Criteria

Inclusion Criteria

- Original, peer-reviewed research studies.
- Studies applying AI technologies in malaria vector control.
- Studies conducted in Kenya, Uganda, Tanzania, Rwanda, or Burundi.
- Articles published in English.

Exclusion Criteria

- Reviews, conference proceedings, editorials, commentaries, and study protocols.
- Studies not involving AI or not related to malaria vector control.
- Studies conducted outside the East African region (Tanzania, Kenya, Uganda, Burundi and Rwanda).

Databases and Search Method

The search strategy was designed to identify peer-reviewed research studies and grey literature addressing AI-based methods in areas such as vector surveillance, larval habitat mapping, insecticide resistance prediction, and optimization of intervention strategies in Kenya, Tanzania, Uganda, Rwanda, and Burundi.

Databases Searched

The review synthesized studies retrieved from the following databases on 09 June 2025 and did not employ restriction on the time frame of publication to ensure comprehensive coverage of interdisciplinary research:

- PubMed – for biomedical and public health literature.
- Google Scholar – for grey literature and academic articles not indexed in traditional databases.
- ScienceDirect – for multidisciplinary and applied artificial intelligence articles.

- IEEE Xplore – for technical and engineering publications related to machine learning and AI in health and environmental monitoring.

These databases were chosen for their relevance to the interdisciplinary scope of the review, spanning public health, computer science, and geospatial technologies.

Search Strategy

The search strategy combined keywords using Boolean operators to identify studies at the intersection of AI and malaria vector control (Table 1). Platform-specific adjustments were made—such as limiting the number of Boolean connectors for databases like ScienceDirect and IEEE Xplore—to ensure compliance with each platform's search constraints.

All retrieved studies were screened for relevance using the predefined inclusion and exclusion criteria. Each article was first evaluated based on title and abstract. Full texts (or provided summaries and metadata when full texts were unavailable via the platform) were then assessed for inclusion. Studies were categorized based on whether they:

- Directly addressed integration of AI in malaria vector control (precisely relevant),
- Applied AI in adjacent machine learning and predictive modelling (partially related), or
- Discussed AI in health or malaria vector control without methodological ties to AI-driven data workflows (distantly related).

Only those falling into the "precisely relevant" or "partially related with methodological focus" categories were retained for synthesis.

Quality Assessment

Each included study was evaluated for quality using criteria adapted from prior PRISMA-ScR guidelines and methodological soundness:

- Clarity of objectives related to AI and malaria vector control.
- Clarity of AI technology used.
- Clarity of malaria vector control area.
- Clarity of country.
- Consideration of key findings, challenges, and future recommendations where applicable.

Studies lacking methodological transparency or not detailing AI application to malaria vector control were down-weighted in the qualitative synthesis.

Data Extraction and Synthesis

A standardized form was used to extract relevant information from the included studies, including: author(s) and publication year, country and study setting, AI technology used, relevance to malaria vector control, key methods/tools, key findings, challenges, and recommendations.

RESULTS

This section presents findings from a scoping review of six research studies conducted in Kenya, Tanzania, and Burundi that explored the application of AI in malaria vector control. The results are structured according to the five research questions converted to key thematic areas guiding the review. All thematic areas in this section are discussed in reference to Table 2.

Article Selection

The systematic search process began with an initial yield of 609 studies across three major databases: PubMed contributed the largest share with 240 studies, followed by Google Scholar with 216 studies, Science Direct 53 and IEEE Xplore 4 studies. Then progressed to screening studies by title and abstract. This screening phase narrowed the pool to 47 full-text studies that underwent comprehensive eligibility assessment. Through rigorous application of our inclusion and exclusion criteria, we ultimately selected 6 studies for final synthesis, as visually documented in the PRISMA-ScR flow diagram (Figure 1). The exclusion process eliminated 40 studies for two primary reasons: First 38 studies were removed for focusing not being relevant to malaria vector control and AI. Second 2 studies were removed for lacking relevance to AI.

Application of Artificial Intelligence in Improving Data Collection and Integration

AI has been employed to enhance data collection and the integration of diverse datasets, including health surveillance, environmental, and entomological information. In Kenya, ensemble modelling (Study 3) was used to combine remote sensing data with larval habitat mapping, improving spatial targeting of control efforts. Similarly, boosted regression techniques in another Kenyan study (Study 6) integrated satellite-derived environmental data with hospital admission records to support malaria early warning systems. In Burundi, statistical predictive modelling (Study 2) utilized national surveillance data to forecast malaria trends, although temporal inconsistencies across data sources posed significant challenges (Table 2). Notably, Uganda and Rwanda were not represented in the included studies. This highlights a regional evidence gap and the limited geographic scope of existing AI applications in malaria vector control in East Africa.

Artificial Intelligence Enhanced Data Analysis in Malaria Vector Control

AI has played a key role in improving data analysis capabilities through predictive modelling and risk estimation. In Tanzania, machine learning models (Study 1) identified key climatic drivers and predicted malaria risk patterns, supporting localized and time-sensitive interventions. In Kenya, Study 6 applied generalized additive models and boosted regression (GAMBOOST) to forecast malaria admissions, demonstrating high predictive accuracy at a one-month lead time. Study 3's use of ensemble modelling significantly enhanced spatial prediction of mosquito larval habitats (Table 2). Overall, despite limited evidence from this region, the few studies reported here demonstrates AI techniques have enhanced analytical depth and spatial resolution in malaria vector control modelling, allowing for more targeted and efficient strategies.

Contributions of Artificial Intelligence to Predictive Accuracy and Operational Efficiency

Artificial intelligence and machine learning methods have contributed to operational improvements by automating complex entomological tasks and enhancing predictive accuracy. In Tanzania, the combination of mid-infrared spectroscopy and machine learning (Study 4) accurately classified mosquito feeding status, automating what is typically a labour-intensive laboratory process. ML classifiers in Study 5 similarly demonstrated high accuracy in determining mosquito age categories, a factor critical for understanding transmission potential (Table 2). These applications contribute directly to improving operational efficiency and precision targeting in vector control, reinforcing AI's value in routine malaria surveillance and intervention planning.

Reported Challenges and Recommendations for Artificial Intelligence Implementation

Despite the promise of AI, several studies reported common implementation challenges. Data-related issues were pervasive, including limited access to high-resolution environmental and health datasets (Study 1), incomplete surveillance data (Study 2), and poor temporal alignment between environmental and hospital data (Study 6). Technical limitations were also noted: Study 4 reported misclassification due to overlapping spectral features, while Study 3 faced difficulty accessing and validating predicted larval habitats on the ground (Table 2). Recommendations across the studies included improving data quality and interoperability, expanding ML training datasets, automating environmental data integration, and fostering intersectoral collaboration. These challenges highlight the need for robust infrastructure and locally adapted AI approaches to realize the full benefits of AI in malaria vector control in the region.

Future Prospects of Artificial Integration in Malaria Vector Control

The reviewed studies suggest promising future directions for artificial integration in malaria control across East Africa. Innovations such as AI-powered early warning systems (Studies 1, 6), automated vector classification tools (Studies 4, 5), and spatial mapping of larval habitats (Study 3) represent scalable solutions for adaptive vector control (Table 2). Additionally, the integration of AI with environmental monitoring and national health systems offers a pathway for more responsive and data-driven interventions.

FIGURE 1: PRISMA Flow Chart for Article Selection Process

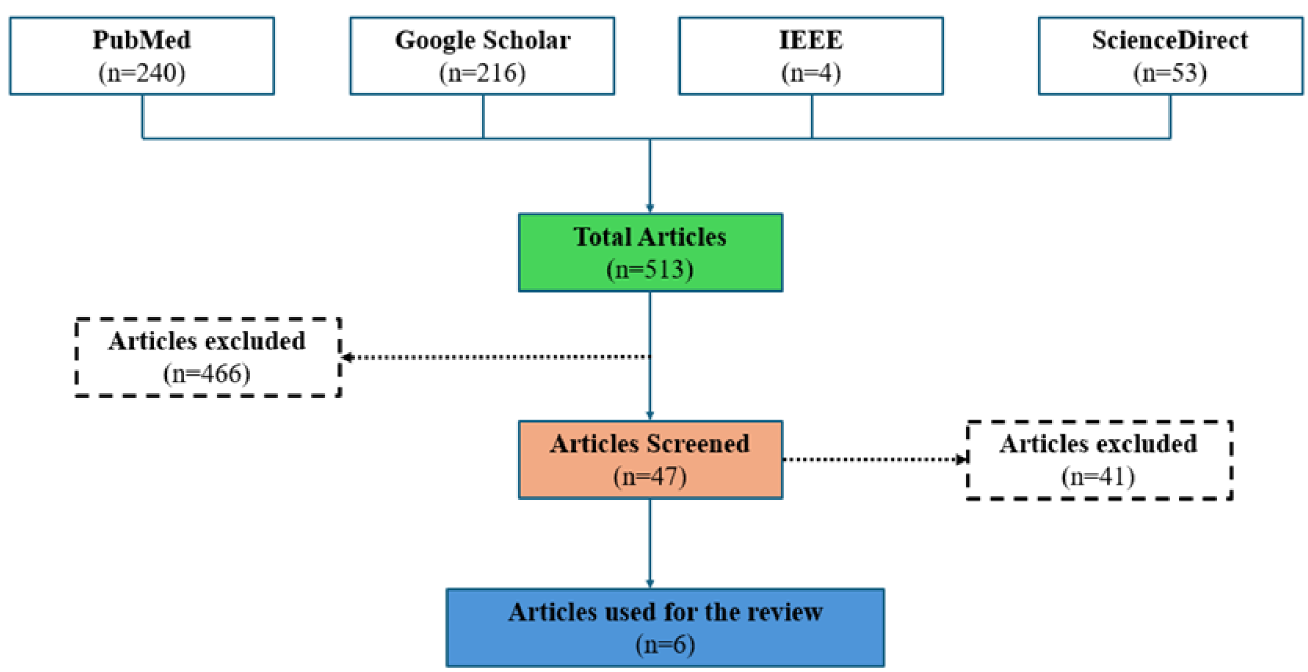

TABLE 2: Research Studies Included in the Review with Key Synthesised Parameters

Study ID	Study Title, Year	Country	AI Technology Used	Focus	Relevance to Malaria Vector Control	Key Methods/ Tool	Key Findings	Challenges	Recommendations
1	Deciphering the Climate-Malaria Nexus: A Machine Learning Approach in Rural South eastern Tanzania, 2024	Tanzania	Machine learning	Machine learning to understand climate impact on malaria	Supports malaria risk prediction for targeted interventions	Machine learning models analyzing climate and malaria data	Identified key climate drivers and predicted malaria risk patterns	Limited access to high-resolution and long-term climate and malaria data. Model generalizability affected by local variations.	Improve access to granular environmental & health data. Incorporate ensemble modeling and spatial heterogeneity.
2	Exploring predictive frameworks for malaria in Burundi, 2022	Burundi	Statistical predictive modeling	Developing predictive models for malaria transmission	Supports malaria early warning systems	Statistical and predictive modeling	Model frameworks developed for malaria forecasting	Incomplete surveillance data. Temporal lags between data sources.	Enhance surveillance data quality. Use integrated data pipelines across ministries.
3	Mapping Potential Malaria vector Larval Habitats for Larval Source Management in Western Kenya: Introduction to Multimodel Ensembling Approaches, 2024	Kenya	Ensemble modelling	Larval habitat prediction using multimodel ensembling	Advances larval control strategies	Multi-model ensemble modelling	Improved prediction accuracy for larval habitats	Limited ground-truth larval data. Inaccessibility of some mapped habitats.	Combine remote sensing with community mapping. Prioritise field validation of high-risk areas.
4	Rapid assessment of blood-feeding histories of wild-caught malaria mosquitoes using mid-infrared spectroscopy & machine learning, 2024	Tanzania	Mid-infrared spectroscopy combined with machine learning	Use of mid-infrared (MIR) spectroscopy & machine learning to identify mosquito feeding history	Enhances understanding of mosquito behaviour	MIR spectroscopy, machine learning	Successfully classified feeding status of mosquitoes	Misclassification due to overlapping spectral features. Small training sample sizes.	Expand training datasets for ML models. Validate with gold-standard lab methods.
5	Rapid classification of epidemiologically relevant age categories of Anopheles funestus, 2024	Tanzania	Machine learning classification	Age classification of malaria vector	Helps assess vector population age structure	Machine learning classification techniques	Accurate age category classification	Age determination overlaps between groups. Field conditions may affect data accuracy.	Improve spectral calibration procedures. Develop robust, low-cost field-ready tools.
6	Using remote sensing environmental data to forecast malaria incidence at a rural district hospital in Western Kenya, 2024	Kenya	Boosted regression machine learning	Malaria incidence forecasting with remote sensing environmental data	Early warning system development	General additive model (GAM), boosted regression (GAMBOOST), satellite data	GAMBOOST at 1-month lead time best predicted malaria admissions	Delays in satellite data processing. Poor alignment between hospital & environmental data timelines.	Automate environmental data integration. Foster collaboration between meteorological & health sectors.

TABLE 1: Search Strategy Keywords & Syntax

Database	Search Keywords & Syntax
PubMed	("artificial intelligence"[Title/Abstract] OR "machine learning"[Title/Abstract] OR "deep learning" [Title/Abstract] OR "predictive model*"[Title/Abstract] OR "data science"[Title/Abstract] OR "digital technology"[Title/Abstract] OR "remote sensing"[Title/Abstract] OR "new technology" [Title/Abstract]) AND ("vector control"[Title/Abstract] OR "malaria control"[Title/Abstract] OR "mosquito control"[Title/Abstract] OR "malaria surveillance"[Title/Abstract] OR "entomological surveillance"[Title/Abstract] OR "malaria vector surveillance"[Title/Abstract] OR "insecticide resistance"[Title/Abstract] OR "Anopheles"[Title/Abstract] OR "LLIN"[Title/Abstract] OR "IRS"[Title/Abstract]) AND ("Kenya"[Title/Abstract] OR "Tanzania"[Title/Abstract] OR "Uganda" [Title/Abstract] OR "Rwanda"[Title/Abstract] OR "Burundi"[Title/Abstract] OR "East Africa" [Title/Abstract])
Google scholar	("artificial intelligence" OR "machine learning" OR "deep learning" OR "predictive model*" OR "data science" OR "digital technology" OR "remote sensing" OR "new technology") AND ("vector control" OR "malaria control" OR "mosquito control" OR "malaria surveillance" OR "entomological surveillance" OR "malaria vector surveillance" OR "insecticide resistance" OR "Anopheles" OR "LLIN" OR "IRS") OR "larvici*" OR "larval source management" OR "house screen* OR "eave*" AND ("Kenya" OR "Tanzania" OR "Uganda" OR "Rwanda" OR "Burundi" OR "East Africa") NO review NO opinion NO editorial NO commentary

DISCUSSION

This scoping review synthesized existing evidence on the application of AI in malaria vector control across East Africa, with a focus on Kenya, Tanzania, Burundi, and an observed gap in Uganda and Rwanda. The reviewed studies demonstrate a growing, though still emergent, body of research exploring how AI technologies can improve malaria control efforts through enhanced data collection, integration, analysis, and prediction.

Emerging Evidence of Artificial Intelligence Applications in Vector Control

The evidence indicates that AI has been primarily applied in three domains: predictive modelling, vector behaviour analysis, and data integration. Machine learning (ML), statistical forecasting, and ensemble modelling were leveraged to develop malaria early warning systems, predict larval habitats, and assess transmission risk based on climatic and surveillance data. [23–26] In addition, AI was employed in entomological research using classification models and mid-infrared spectroscopy to determine mosquito feeding status and age structure, [27,28] contributing to improved understanding of transmission dynamics. Notably, the AI applications extend beyond basic forecasting to address spatial heterogeneity, nonlinear trends, and environmental drivers of transmission areas where traditional models often fall short. These innovations hold the potential to support more targeted interventions, especially in settings where resources are limited and timely decision-making is essential. However, the relatively small number of studies identified, only six across five countries, indicates that the integration of AI into malaria vector control remains in its early stages in the region.

Challenges Limiting Implementation and Impact

Despite promising developments, several challenges constrain the broader adoption and scalability of AI in malaria control programs. Data-related barriers were the most commonly reported limitations, [23–26,28] These include poor access to high-resolution environmental data, incomplete surveillance data, small training sample sizes for ML models, and temporal misalignment between health and environmental data sources. These challenges undermine the performance and generalizability of AI models and reflect broader issues in health data governance across the region.

Technical and operational limitations further complicate implementation. For example, misclassification errors in AI-driven entomological tools, [28] limited field validation, [25] and the inaccessibility of some predicted high-risk sites limit the translation of AI outputs into actionable public health responses. Moreover, the reviewed studies highlighted a lack of robust field-ready tools and insufficient coordination between sectors (e.g., meteorological and health ministries), underscoring the need for improved institutional integration and local capacity building.

Gaps and Future Directions

Taken together, the evidence suggests that AI is poised to play an increasingly pivotal role in malaria vector control strategies in East Africa. However, the number of empirical studies operationalizing AI within real-world malaria control workflows remains limited. Much of the current literature emphasizes model development or technical potential, with fewer studies demonstrating sustained implementation, impact assessment, or scalability.

This review highlights key gaps that signal a shift in future research and policy priorities:

- From isolated pilot studies to coordinated, multi-country AI implementation initiatives.
- From technical modelling to integrated public health systems where AI tools are embedded within national malaria vector surveillance, and early warning infrastructures.
- From raw predictive performance to practical utility,

with emphasis on field usability, cost-effectiveness, and alignment with national malaria control strategies.

- From data scarcity to data governance, encouraging investment in local data ecosystems, interoperability standards, and ethical AI practices that protect privacy and promote equity.

Despite the emergent nature of AI applications in malaria vector control, the studies reviewed indicate significant promise in enhancing forecasting precision, resource allocation, and automation of entomological tasks. Yet consistent with the scoping approach, this review also surfaces foundational barriers, especially around data access, inter-sectoral collaboration, and sustainable deployment models, that must be addressed to fully realize AI's potential. Looking ahead, a more inclusive, context-sensitive, and operationally grounded approach to AI deployment is essential. Bridging the gap between technical innovation and public health impact will require not only novel algorithms, but also thoughtful governance, participatory design, and strong regional coordination.

Limitations

Several important limitations merit consideration when interpreting this review's findings. The geographic scope was constrained, with eligible studies identified only from Kenya, Tanzania, and Burundi, excluding Uganda and Rwanda, thereby limiting the regional completeness of the evidence base. The temporal coverage and reliance on mainstream academic databases may have omitted relevant grey literature, technical reports, or preprints that often showcase emerging artificial intelligence applications. The included studies showed substantial methodological heterogeneity, employing various AI techniques across differing malaria control objectives, which complicated direct comparisons and synthesis. Additionally, most studies focused on technical feasibility or predictive modelling without validating AI applications in real-world malaria control settings. Lastly, consistent with the scoping review approach, no formal quality appraisal was conducted, which limits conclusions about the methodological robustness of individual studies.

CONCLUSION

This review highlights the emerging role of AI in enhancing malaria vector control efforts in East Africa, particularly through improved prediction, surveillance, and decision-making tools. While AI applications show significant promise, especially in data integration and early warning systems, their implementation remains limited, with notable regional gaps and operational challenges. Future work should focus on translating existing innovations into field-ready tools, expanding research across underrepresented countries, and fostering cross-sector collaboration to ensure AI contributes meaningfully to malaria vector control with elimination goals.

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