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CORRESPONDENCE

Ethical and equitable approaches in AI for vector-borne disease management

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Abstract
Artificial intelligence (AI) is increasingly being incorporated into public health strategies for vector-borne disease (VBD) management, offering several advances in surveillance, prediction, and control. At the same time however, the integration of AI technologies raises critical ethical and equity concerns, particularly in regions disproportionately affected by VBDs. Here, we explore seven key ethical and equitable challenges in the use of AI for VBD management: (1) data quality and representativeness, (2) risk of discrimination and inequality reinforcement, (3) transparency and reproducibility, (4) privacy and data protection, (5) cybersecurity, (6) fair and equitable benefit-sharing, and (7) environmental considerations. Within each of these challenges, we highlight how unaddressed ethical and equity issues can exacerbate health disparities and undermine public trust. We then propose actionable pathways forward, including inclusive data governance, transparency-enhancing tools, and environmentally-conscious AI practices. By highlighting how accounting for these ethical and equity concerns during AI development and deployment can further progress towards the United Nations Sustainable Development Goals, we advocate for a more responsible and inclusive approach to AI in VBD management.

Keywords Artificial intelligence · Ethics · Equity · Infectious disease · Public health · Vectors

1 Introduction

The rapid integration of artificial intelligence (AI) into public health strategies presents transformative opportunities to enhance the precision, efficiency, and scalability of interventions [1]. Yet, these advances also raise complex ethical and equity concerns that require careful consideration and proactive governance [2]. Vector-borne diseases (VBDs) are infectious illnesses affecting humans and other vertebrates caused by viruses, parasites, or bacteria transmitted by living organisms (vectors), and are particularly challenging 'wicked problems' in public health [3, 4]. These diseases are responsible for over 700,000 deaths annually, with the burden falling disproportionately on populations in tropical and subtropical regions [5]. The integration of AI into VBD control offers powerful tools for surveillance, prediction, and control (Table 1), and is rapidly gaining attention [6, 7].

Public health interventions have a direct impact on individual and community well-being, making ethical and equitable scrutiny essential. Traditional bioethical principles–autonomy, non-maleficence, beneficence, and justice–remain a foundational lens for evaluating AI in healthcare [17]. However, the distinctive features of AI, its opacity, autonomous learning capacity, and reliance on vast datasets, introduce novel ethical dimensions and arising inequalities. These issues highlight the need for ethically and equitable aligned design, deployment, and regulation of AI tools in both local and global health contexts, particularly where vulnerabilities are greatest. This will not only help prevent the deepening of existing inequalities, but also build on the capacity of AI to support the achievement of the United Nations Sustainable Development Goals [18].

Here, we expand previous ethical and equitable discourses to discuss critical issues that developers and users of AI in VBD control must consider. In this paper, we

Extended author information available on the last page of the article

Table 1 Examples of AI integration in vector-borne disease surveillance and management

Research area	AI example
Prediction	
Remote sensing	Youssefi et al. predicted the location of larval habitats of *Anopheles* mosquitos using remote sensing, soil type data, and land-use maps, the latter of which were produced using Support Vector Machine classification [8].
Population dynamics	Zhang et al. developed a combined framework integrating mechanistic differential equations with a neural network to model *Aedes* mosquito population dynamics [9].
Modelling disease drivers	Farooq et al. used extreme gradient boosting along with explainable AI (XAI) to identify environmental drivers of West Nile virus [10].
Surveillance	
Species identification	Wang et al. used an AI-powered system that employed Segment Anything Method for image preprocessing and leveraged Faster Region-based Convolutional Neural Network for robust mosquito species detection in complex outdoor environments [11].
Mechanical control	The VECTRACK system integrates infrared optical sensors with supervised machine learning algorithms – specifically Random Forest and Gradient Boosting classifiers – to analyse wingbeat frequencies and classify adult mosquitoes by genus (*Aedes* or *Culex*) and sex with high accuracy. Micocci et al. combined a commercial trapping device, BG-Mosquitaire trap, with the VECTRACK system [12].
Citizen science	Pataki et al. used a deep learning model to identify tiger mosquitoes (*Aedes albopictus*) in images from the Mosquito Alert citizen science system [13].
Control	
Insecticides resistance monitoring	Qureshi et al. used XAI to differentiate flight trajectory patterns between insecticide-susceptible and -resistant strains of *Anopheles gambiae*, which can be used to inform intervention strategies [14].
Sterile insect technique (SIT)	Sex-sorting is a key stage of SIT programmes. Naranjo-Alcazar et al. used machine learning techniques to refine this process by differentiating between male and female mosquitoes using flapping sounds [15].
And	
Incompatible insect technique (IIT) strategies	Advanced computer vision techniques were employed by Crawford et al. to facilitate the automated and high-throughput sex separation of *Wolbachia*-infected mosquitoes within the framework of an IIT programme. The integration of AI ensured the exclusive release of male specimens, thereby minimizing the risk of inadvertently releasing fertile females [16].

focus on AI software (encompassing data, code, and models), and do not address hardware-related issues, although many of the ethical and equity considerations discussed are applicable to both. By applying established AI ethics and equity principles specifically to the high-stakes context of VBDs, we explore challenges across surveillance, modelling, and intervention strategies, and provide pathways forward tailored to VBD-specific data, systems, and vulnerable populations. The seven key and interlinked issues we discuss are: (1) data quality and representativeness, particularly in underserved regions where data gaps may reinforce health inequities, (2) risk of discrimination and reinforcement of inequalities, arising from unrepresentative training data or flawed algorithmic assumptions, (3) algorithmic transparency and reproducibility of AI models, critical for accountability and public trust, (4) privacy and data protection, especially given the sensitivity of geolocation and health data, (5) cybersecurity, ensuring that AI systems are safeguarded against misuse or malfunction, (6) fair and equitable benefit-sharing, to prevent the concentration of technological advantages in already privileged settings [19], and (7) environmental considerations underlying the use of AI technologies in VBD control, in which the infrastructure requirements are an inextricable ethical component of the software, and critical to consider as we strive to bend the curve of biodiversity loss and combat climate change (Fig. 1) [20]. We conclude by presenting ways in which promoting ethical and equitable use of AI in VBD research and control can help us reach the SDG goals. By summarising these key challenges and proposing actionable pathways forward, this work provides a novel synthesis that applies AI ethics and equity principles specifically to VBD management. Our goal is to guide developers, policymakers, and public health practitioners in deploying AI for VBD control responsibly, ensuring that technological innovation advances public health while also protecting the well-being of people and the planet.

2 Data quality and representativeness

2.1 Challenges: data gaps and bias in underserved regions

Robust AI systems require high-quality, representative, and contextually relevant data, particularly in health domains where decisions affect individual and public safety [21]. In VBD management, poor data quality or biased datasets can lead to models with limited validity and potentially harmful outcomes [22]. This issue is exacerbated by the inherent heterogeneity of VBDs across geography, ecology, socioeconomic conditions, and clinical presentation. Incomplete or skewed data can result in inaccurate risk maps, ineffective interventions, or misallocation of limited resources. A cautionary case is IBM's *Watson for Oncology*, which generated "unsafe and incorrect" treatment recommendations due

Fig. 1 Conceptual figure showing the interconnections among the seven ethical and equity issues discussed (circled). Although not an exhaustive map of all possible relationships, the labeled arrows indicate areas of overlap and illustrate how proposed pathways forward can generate positive outcomes across multiple issues. Vector image credits: NIAID NIH BIOART SOURCE. [658-459-138-267]

to training on artificial, non-clinical data rather than validated real-world datasets [23]. This example underscores the critical need for rigorous data validation when developing AI systems for health-related applications.

In the context of VBDs, data gaps are even more severe. Many endemic regions for malaria, dengue, or Zika suffer from limited surveillance infrastructure, underreporting, and inconsistent data collection practices [e.g., 24]. According to the WHO, over 60% of countries affected by VBDs lack adequate systems for routine entomological and epidemiological data collection [25].

Addressing these data limitations is essential to ensure that AI tools enhance, rather than undermine, the effectiveness and equity of vector control strategies. High-quality, representative, and contextually rich data are essential to ensure that AI models are reliable, equitable, and generalisable–particularly in the highly heterogeneous domain of VBDs.

2.2 Pathways forward: inclusive, quality data collection and contextual validation

Improving data quality for AI-driven vector control requires a multifaceted and proactive approach, spanning technical, methodological, institutional, and strategic dimensions.

Technically, the adoption of standardised protocols for data collection, annotation, and validation significantly enhances consistency and compatibility across datasets [26]. Automated tools for anomaly detection and metadata quality control are essential for identifying and addressing errors early, ensuring the long-term integrity of datasets.

Methodologically, techniques such as active learning and few-shot learning offer pathways to build robust models even when high-quality data is limited [27]. Additionally, data augmentation and generative models can expand dataset variability and representativeness of training datasets, enabling more accurate and generalisable AI outputs [28].

Institutionally, collaborative networks and data-sharing initiatives play a central role in overcoming disparities in data availability across regions. Successful examples include the Malaria Atlas Project (https://malariaatlas.org/) and the Global Vector Hub (https://globalvectorhub.lshtm.ac.uk/), which illustrate how pooling resources and expertise across institutions can produce high-resolution, globally relevant datasets [29].

Beyond data quality and structure, data sufficiency is a fundamental requirement for viable AI development [30]. Models require minimum volumes and coverage across key variables (such as sex, age, socioeconomic status, and region) to avoid bias and ensure that outputs are reliable and broadly applicable. While precise thresholds are context-dependent, insufficient or unbalanced datasets can result in skewed predictions and suboptimal decision-making, especially for underserved or vulnerable populations [31]. In this scenario, the use of synthetic data for training AI systems represents a highly promising strategy to expand datasets that require larger volumes of information, while simultaneously overcoming cost-efficiency barriers and offering a more privacy-preserving solution [32]. In contrast to real-world data, which often involve substantial expenses for collection, storage, and annotation, and may raise significant ethical and legal concerns regarding sensitive information, synthetic data can be generated at scale through algorithms, generative models, or simulations that replicate the characteristics of real data [33]. This approach not only reduces financial and logistical constraints but also provides strong safeguards against privacy breaches, as no actual personal or confidential records are exposed [34]. In addition, it can constitute a more respectful alternative when working across diverse cultures, particularly in cases where invasive or sensitive techniques are required to obtain samples. Moreover, when rigorously validated, synthetic datasets support the development of AI systems with robust and reliable statistical performance. Nonetheless, ensuring their quality and integrity remains critical, particularly by addressing the risks of hallucinations and bias amplification, in order to secure their trustworthiness in real-world applications [32, 35].

In addition to refining existing datasets, there is a need to actively address data gaps through targeted and inclusive strategies. These include (i) targeted data collection campaigns in high-priority, underrepresented regions; (ii) capacity-building programs to strengthen local surveillance infrastructure and data systems; (iii) incentives for data sharing from non-governmental organisations (NGOs), academic institutions, and governmental bodies, supported by clear governance and mutual benefit frameworks; and (iv) participatory data collection models, such as citizen science and community-based monitoring [36–38], to engage local actors and reach populations often overlooked by conventional surveillance. These strategic interventions are essential to shift from passive data reliance to proactive data governance, and close geographic and demographic gaps that currently limit the effectiveness of AI tools.

Together, technical refinement, methodological innovation, institutional collaboration, and strategic outreach form a cohesive roadmap for developing trustworthy, accurate, and inclusive AI systems in VBD control. These efforts not only improve model performance but also advance global health equity by ensuring that AI-driven interventions are based on data that reflect the full spectrum of human and environmental diversity.

3 Risk of discrimination and reinforcement of inequalities

3.1 Challenges: structural bias and algorithmic discrimination

AI systems trained on historical data risk reproducing or amplifying existing social biases, particularly in healthcare, where socioeconomic and geographical disparities are already pronounced [23]. A study by Obermeyer et al. exposed such bias in a widely used U.S. healthcare algorithm, which underestimated the needs of Black patients despite identical clinical profiles [39]. The cause: reliance on healthcare spending as a proxy for need, an apparently neutral variable that in fact encoded systemic inequities. This risk of biased AI algorithms influences public attitudes towards AI use in healthcare, and was highlighted as a particular challenge during responses to the COVID-19 pandemic [40]. In VBD control, the risk of amplifying existing social biases is magnified by the strong correlation between poverty, ethnicity, and exposure to vectors in many endemic regions.

In the context of AI-driven vector surveillance and intervention, discrimination can emerge via several interlinked mechanisms. First, through data underrepresentation, since marginalised communities often lack adequate epidemiological data coverage, leading to lower model accuracy and biased predictions for these populations [31]. Second, due to predictive disparity, whereby AI systems perform better for well-represented or digitally connected populations, which creates uneven intervention effectiveness [41]. Third, there may be implicit bias in design. Even with representative data, model developers' assumptions can introduce structural bias, such as through variable selection, risk thresholding, or classification schemes that inadvertently penalise disadvantaged groups [41]. Fourth, there is a digital divide [42]. Inequities in access to digital infrastructure result in uneven benefits from AI interventions, privileging affluent areas with reliable connectivity while leaving behind underserved regions. Addressing these issues requires not only technical corrections but a commitment to equity-aware model development and inclusive data practices.

3.2 Pathways forward: equity-centred design and bias auditing

Effectively addressing the risk of discrimination in AI systems designated for VBD control requires a multifaceted approach that again integrates multiple dimensions. At the algorithmic level, implementing bias detection and mitigation techniques is essential. These include: (i) data debiasing (e.g., reweighting or resampling to correct for underrepresentation); (ii) fairness-aware learning algorithms, which incorporate fairness constraints directly into model optimisation, and (iii) post hoc calibration techniques to adjust outputs and improve parity across demographic groups [43]. Such tools help identify and rectify disparities in model predictions before deployment.

At the methodological level, participatory model development can play a critical role in anticipating and reducing discriminatory outcomes [44]. This includes: (i) community engagement in the co-design, validation, and field testing of AI tools, (ii) inclusion of stakeholders from diverse geographic and socio-economic backgrounds, and (iii) participatory auditing, enabling those most affected by the systems to contribute to bias detection and risk assessment [45]. Such inclusion enhances model transparency and contextual relevance. However, caution is required when offering financial incentives in VBD studies. For instance, in a Kenyan malaria human infection study, payments were a primary motivation for volunteer participation, raising concerns that some individuals may try to hide symptoms to maximise payments [46]. Lessons should also be learnt from the deployment of AI in other healthcare situations, such as the COVID-19 pandemic [40, 47].

At the regulatory level, the establishment of clear ethical and legal standards is vital to ensure accountability. This includes: (i) regulatory guidelines that mandate fairness audits, demographic impact assessments, and continuous monitoring of AI performance in real-world applications, (ii) documentation requirements (e.g., model cards, datasheets for datasets [see below]) that enhance transparency, and (iii) equity-focused oversight mechanisms, especially in public health deployments [48]. These frameworks should aim to protect vulnerable populations and ensure that AI tools serve public health goals equitably.

4 Algorithmic transparency and reproducibility of AI models

4.1 Challenges: the "black box" problem in complex AI systems

Transparency and reproducibility are foundational prerequisites for building trust and ensuring responsible use of AI systems in healthcare, particularly when their outputs influence public health interventions and resource allocation [49, 50]. However, many advanced AI models, especially those based on deep learning, are often characterized as "black boxes", as their internal decision-making processes are opaque and difficult to interpret without additional explanation [51].

This lack of interpretability presents a substantial challenge in the field of VBD control, where predictive models must account for a complex interplay of environmental, epidemiological, socio-economic, and behavioural factors. Deep neural networks, for example, may achieve high accuracy, but the underlying reasoning remains difficult to disentangle, making it challenging to assess whether predictions are based on causally meaningful associations or misleading correlations [52]. In public health contexts, this opacity can undermine accountability, obscure embedded biases, and limit the capacity for expert validation [1]. Furthermore, this lack of transparency can cause policy or industry stakeholders to misunderstand or misinterpret data, potentially resulting in ineffective interventions. This issue is exacerbated by the limited availability of data and code: important datasets and models are frequently unavailable due to proprietary limitations, institutional control, or placement behind paywalls. Such practices not only block reproducibility but also reinforce structural inequalities, allowing well-resourced institutions to dominate research while limiting participation of researchers in locations most affected by VBDs from meaningful involvement [53].

Historical cases illustrate how ethical gaps in vector-borne disease interventions can deepen mistrust and amplify structural inequalities, particularly in communities already marginalized by health system failures. During the Zika outbreaks in Brazil and Puerto Rico, pregnant women were enrolled in vector control and surveillance programs without consistent informed consent, while public communication downplayed uncertainties and potential reproductive health risks [54, 55]. Similarly, the Philippines' Dengvaxia vaccination program exposed thousands of seronegative children to an increased risk of severe dengue because of insufficient pre-vaccination screening, reliance on short-term efficacy data, and inadequate post-implementation monitoring. These cases, and many others documented globally, demonstrate how poor risk communication, opaque decision-making, and inequitable community engagement can produce long-lasting harm [56, 57]. Such lessons underscore the necessity of transparency, accountability, and ethical reciprocity when introducing new technologies, including AI-based systems, into VBD management.

Benchmarks and model evaluation also raise related concerns, as their quality depends on their design and usability [58]. Decisions concerning what qualifies as a valid standard, who maintains it, and whose interests it reflects are rarely apparent. As a result, evaluation criteria risk being formed by the interests of a limited set of stakeholders rather than the different circumstances in which interventions must be implemented. These dynamics may shift VBD modelling away from an open scientific pursuit and unintentionally reinforce inequities by concentrating influence over information creation and decision-making among a narrow group of actors.

4.2 Pathways forward: enhancing transparency and reproducibility

Starting with technical solutions, the development of Explainable AI (XAI) techniques is a crucial step forward in addressing the transparency deficit of AI systems. Tools such as LIME (Local Interpretable Model-agnostic Explanations), SHAP (SHapley Additive exPlanations) and model-specific attention mechanisms can provide interpretable, local explanations of model behaviour, revealing which features most influenced a given prediction [59]. For example, a recent machine learning model combined with XAI was applied to dengue outbreak forecasting in Bangladesh and demonstrated gains in both interpretability and predictive accuracy [60]. These approaches can help users and stakeholders understand the decision logic, even in complex models. However, they do not fully reveal the underlying reasoning, which can leave important decisions still partially opaque. In some cases of machine learning where it is difficult to adopt XAI, the result should be reported on the prediction on an external dataset [61], or more robust overfitting strategies such as cross-validation and early termination of training should be implemented to prevent the result from being overestimated [62].

Next, considering methodological choices, in cases where decision transparency outweighs the marginal gains of predictive performance, opting for inherently interpretable models (such as decision trees, rule-based systems, or Bayesian networks) may be preferable [63]. Especially in critical public health applications, the comprehensibility and auditability of these models can enhance legitimacy, improve stakeholder trust, and enable more informed policy decisions.

Last, it is critical that there are standardised documentation practices. Initiatives such as "Datasheets for Datasets" [26] and "Model Cards for Model Reporting" [64] contribute to reproducibility and accountability by promoting rigorous documentation of dataset properties, model design, training procedures, evaluation metrics, and known limitations. These frameworks facilitate transparency throughout the AI pipeline and enable meaningful cross-contextual evaluation and replication.

5 Privacy and data protection

5.1 Challenges: vulnerabilities in sensitive health and location data

AI systems for VBD management typically rely on extensive datasets containing potentially sensitive information, including epidemiological, demographic, geographic, and occasionally genetic data. The reliance on big data introduces significant privacy risks for individuals and communities involved [65]. A key concern is re-identification. Even anonymised dataset can be linked with external sources to re-identify individuals, particularly when they include precise geolocation data or rare demographic profiles [66]. This risk is especially acute in sparsely populated rural areas, where unique data combinations can easily point to specific households.

Community stigmatisation presents another major challenge. Predictive models identifying certain groups as high-risk, though statistically sound, may lead to social or economic discrimination, for example in housing, tourism, or investment sectors. This disproportionately affects already vulnerable populations [67]. The centralisation of sensitive data also raises the threat of unauthorised access. Aggregated health, demographic, and location data are attractive targets for malicious actors, posing risks of identity theft and commercial misuse [68]. A more insidious risk is function creep, where data collected for legitimate public health purposes are later repurposed without individuals' knowledge or consent [69]. Such practices erode public trust and may undermine future participation in health initiatives.

Finally, the cross-border nature of VBDs necessitates international data sharing. However, disparate legal frameworks across jurisdictions complicate the enforcement of consistent privacy safeguards [70].

5.2 Pathways forward: ethical data governance and privacy-preserving techniques

Mitigating privacy risks in AI-based public health interventions demands integrated technical, legal, and ethical solutions. From a technical perspective, privacy-enhancing technologies such as differential privacy, federated learning and homomorphic encryption offer promising tools to extract insights from sensitive data without directly sharing it [71]. These methods reduce risks of re-identification and unauthorised access while preserving data utility.

On the legal front, robust and harmonised regulatory frameworks are essential. These must account for the specific challenges of AI in health applications and balance individual privacy rights with the public good [48]. Guidance could be taken from frameworks focused on genetically modified insects for VBD management [e.g., 72].

Ethically, the implementation of informed consent and data stewardship principles is crucial. This entails clear communication about data use, potential risks and benefits, and strict access and management controls [65]. Transparency and accountability are vital to maintaining public trust.

6 Cybersecurity

6.1 Challenges: risks of system misuse and malfunction

AI systems used in public health, particularly in VBD control, carry inherent safety risks due to their influence on health interventions and resource allocation. These risks are exacerbated by cybersecurity vulnerabilities that affect many digital health infrastructures. One major threat is adversarial attacks: subtle, malicious input modifications can mislead AI systems into making incorrect predictions or classifications [73]. In the context of VBD control, this can result in flawed risk assessments and misdirected prevention resources, increasing exposure for high-risk populations and wasting capacity on low-priority regions.

Another serious concern is data poisoning, where manipulated inputs are injected into training datasets, particularly dangerous for systems that adapt to real-time data [74]. Such attacks can gradually degrade model performance in ways that evade standard quality control mechanisms. Even in the absence of malicious intent, systemic errors pose a constant risk. AI systems may fail when exposed to edge cases or out-of-distribution inputs–exactly the scenarios that arise during outbreaks or vector incursions into new regions, when accurate predictions are most critical [75]. Finally, the integration of AI systems into critical healthcare infrastructure creates new cyberattack surfaces [76]. Compromising these systems could disrupt not only predictive models but also surveillance platforms and coordination networks essential for outbreak response, amplifying risks far beyond individual prediction errors.

6.2 Pathways forward: robust security protocols and ethical safeguards

Improving the safety of AI application in VBD control requires a multi-level approach, integrating technical, procedural, and organisational safeguards. At the technical level, measures such as adversary training, anomaly detection, and continuous performance monitoring are essential to detect and mitigate attacks or failures in real time [77].

Procedural safeguards should include robust validation and verification protocols before deployment in high-stakes settings. These should include stress-testing with edge-case scenarios and diverse datasets to assess system robustness under uncertainty and, consequently, enable us to produce more trustworthy AI systems [75].

At an organisational level, fostering a safety-first culture and implementing a comprehensive risk management framework are critical [78]. Key components include ongoing staff training, transparent incident reporting, and proactive identification and mitigation of vulnerabilities before exploitation occurs.

7 Fair and equitable benefit-sharing

7.1 Challenges: unequal access and the global digital divide

While advanced AI technologies offer considerable promise for improving VBD control, their benefits are often inequitably distributed. Global disparities in technological infrastructure, expertise and financial resources mean that privileged populations are most likely to benefit, whereas communities with the highest disease burden, notably in sub-Saharan Africa, Southeast Asia, and parts of Latin America, frequently lack access to these tools [79].

This digital divide may also reflect cultural barriers and personal beliefs, leading to different levels of acceptance and uptakes of AI technologies [42]. The paradox is stark: those who would benefit most from AI innovations, due to limited conventional resources, are often the least likely to access or adopt them [80]. Without deliberate attention to these disparities, AI deployment may reinforce existing inequities, undermining global health goals, and weakening trust in technological solutions.

Furthermore, high-quality entomological and epidemiological datasets from low- and middle-income countries (LMICs), such as mosquito images, vector maps, and surveillance data, are often used by institutions in high-income regions to develop AI tools [e.g., 81]. Yet, the individuals and communities who contribute these resources often receive limited recognition in the form of authorship, financial reward, or timely access to resulting interventions [82, 83]. This imbalance raises concerns about fairness, ownership, and sovereignty, and without mechanisms for equitable benefit-sharing, AI applications risk reinforcing extractive patterns of knowledge production instead of promoting genuine partnerships for health equity.

7.2 Pathways forward: participatory innovation and equitable partnerships

Addressing inequality in AI access requires a multidimensional strategy. At the technical level, AI tools must be designed for low-resource settings [84]. This includes systems optimised for limited computing capacity, intermittent connectivity, and minimal technical support, enabling their use in remote or underdeveloped areas. Examples of ongoing work designing such tools includes work by Kimutai and Förster [85], who produced a low-cost TinyML model that enabled mosquito repellent to be released into a room when an *Anopheles* mosquito was present.

At the economic level, innovative funding mechanisms, including public-private partnerships, philanthropic support, and targeted international development programmes, can help bridge the technology gap [25]. These mechanisms should support not only infrastructure but also capacity-building and training.

At the socio-cultural level, community participation is essential. Engaging local stakeholders in all stages of system development, from design to implementation, ensures cultural relevance, improves acceptance, and increases the effectiveness of interventions [45]. Co-creation with affected communities fosters ownership and trust, both of which are vital for sustainable public health outcomes. An example of the importance of incorporating cultural relevance into VBD management is in the colour selection of insecticidal bed nets in Burkina Faso–green nets achieved higher community uptake than white ones, as white is traditionally associated with local death rituals [86].

At the data governance level, the adoption of FAIR Data Principles can enhance equitable AI applications in VBD control [87]. These principles propose that data should be Findable, Accessible, Interoperable, and Reusable [88]. As such, FAIR Data Principles facilitate cross-disciplinary and cross-border data sharing while strengthening transparency, reproducibility, and accountability in AI systems. However, their implementation must be adapted to local contexts and governance frameworks to avoid reinforcing existing inequalities and to support inclusive participation and fair benefit-sharing [88, 89].

8 Environmental considerations in the use of AI technologies in vector-borne disease control

8.1 Challenges: ecological footprint of AI technologies

As ongoing climate changes lead to shifts in disease vectors [90], the role of AI-driven tools in enhancing the precision and responsiveness of public health interventions is becoming increasingly critical. However, these technological advances come at a cost, with the environmental footprint of AI tools not limited to the algorithms themselves, but also encompassing the supporting computational infrastructure such as servers, cloud servers, and data centres. Consequently, this infrastructure is an inextricable ethical component of the AI software. For example, the high energy consumption and associated emissions from AI data centres contribute to local air pollution and global carbon footprints, disproportionately affecting disadvantaged populations [91]. Han et al. [92] estimate that health damages from AI-related emissions could reach $20 billion annually by 2030, with vulnerable households facing up to 200 times greater burdens. Wierman and Ren [93] also highlight how emissions from data center backup generators worsen respiratory illnesses in marginalized areas. Furthermore, industry data show AI's growing environmental footprint, with companies like Google increasing carbon emissions by 11% in 2024 due to AI workloads [94] and projections indicating AI could account for 3.4% of global CO_2 emissions by 2030 [95]. In addition to energy, AI data centres also require substantial amounts of water [96]. To maximize AI's public health benefits while minimizing environmental harm, it is crucial to invest in energy- and water-efficient AI systems, clean energy sources, and equitable deployment strategies that protect climate-vulnerable communities.

There is also a risk that AI-guided interventions developed with data from high-income countries may lead to unintentional negative ecological effects if applied without local adaptation to ecologically-distinct areas of the Global South [97]. Precision application of insecticides, for example, may pose ecological risks if not grounded in robust local environmental data. Algorithms trained on biased or incomplete datasets may recommend aggressive or ecologically inappropriate control strategies, potentially harming non-target species, ecologically-important species (such as pollinators), or non-target ecosystems [98, 99]. However, actively seeking to fill data gaps can also have unintentional environmental consequences. For instance, deploying unmanned aerial vehicles in natural habitats can interfere with wildlife behavior, and increased human activity for equipment maintenance may alter sensitive breeding sites [99, 100]. Furthermore, large-scale data collection, especially when conducted without community consultation, can infringe upon the ecological sovereignty of Indigenous and rural populations who rely on biodiversity for their livelihoods [100].

Moreover, AI-driven public health decision-making can influence land use and local ecological dynamics. For example, identifying high-risk zones for vector transmission may result in policies that alter access to traditional lands, change agricultural practices, or encourage habitat modification, each of which could lead to biodiversity loss or disruption of traditional ecological knowledge systems [101–104].

8.2 Pathways forward: sustainable AI practices and biodiversity-conscious design

Technological advancement in AI, including both algorithmic design and the supporting computational infrastructure, introduces environmental and ethical considerations that must be addressed to ensure that AI-supported disease control interventions are ecologically responsible and sustainable [97, 105]. This includes developing energy- and water-efficient AI systems, ensuring ecological transparency in algorithmic decisions, and involving local communities and ecologists in co-creating solutions [97, 105]. In recent years there has been growing interest in measuring the environmental impacts of AI, from companies carrying out environmental impact assessments for their AI systems to international policy documents [106]. For AI use in VBD management, project-level reporting of energy, emissions (including co-pollutants), and water, with basic temporal and locational resolution, will allow for more accountable decisions and comparisons across interventions [107].

Around the world, cloud-based personal health platforms have been on the rise. More recently, the concept of a Global Patient co-Owned Cloud (GPOC) has been gaining attention [108–110]. If this global personal record platform were to be adopted, there is potential for this to provide a large substrate for AI development and dissemination [109, 110]. Due to it's more ecological structure, co-ownership model, and ability to increase individual patient empowerment, a GPOC has the potential to not only be a more environmentally-friendly pathway forward, but also help work towards achieving the Sustainable Development Goals [110].

As AI continues to shape the future of VBD surveillance and control, a rigorous environmental lens is essential, especially as we are facing a biodiversity crisis [111]. Environmental variables such as climate trends, biodiversity indices, and land-use change should not only be included in models for prediction but also guide the scope and limitations of interventions [98]. Furthermore, preregistered ecological protocols, co-design with local stakeholders, independent monitoring, and predefined rollback criteria provide a responsible path for iteration, especially where uncertainty is high. This is supplemented by rigorous model transfer techniques such as domain-shift testing, local ground-truthing, and decision-relevant uncertainty reporting, which should ideally begin with time-limited pilot tests before scaling. Through conscientious and inclusive design, AI technologies can serve public health while preserving the integrity of ecosystems upon which both vectors and vulnerable communities depend [97, 99, 112].

9 Ethical and equitable AI in vector-borne disease control and the Sustainable Development Goals

Advancing towards more ethical and equitable use of AI in VBD control and research will likely have far-reaching benefits. Here, we've collated examples of ways in which ethical and equitable AI use align with and promote progress towards the United Nation's 17 Sustainable Development Goals [20].

Sustainable Development Goals (SDG)	Benefits of ethical and equitable AI in VBD control towards the SDG	References
1. **No poverty** End poverty in all its forms everywhere	Integrating AI technologies into VBD control can improve disease prediction and prevention. Ensuring these benefits reach low-income regions can reduce economic losses from illness and, consequently, household poverty.	[10, 113]

Sustainable Development Goals (SDG)	Benefits of ethical and equitable AI in VBD control towards the SDG	References
2. **Zero hunger** End hunger, achieve food security and improved nutrition and promote sustainable agriculture	Reducing VBD burden in vulnerable agricultural communities can help improve agricultural productivity and food security. Improving the transparency of AI systems and tailoring to local contexts may promote farmer trust in interventions derived from AI systems.	[114, 115]
3. **Good health and well-being** Ensure healthy lives and promote well-being for all at all ages	Ensuring that health benefits due to AI-assisted VBD surveillance and targeted interventions reach marginalised populations reduces global health disparities.	[116]
4. **Quality education** Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all	Similar to SDG 2, reducing VBD burden in children can support better performance at school. The equitable use of AI can also support VBD awareness campaigns and education tailored to local contexts.	[117, 118]
5. **Gender equality** Achieve gender equality and empower all women and girls	Ethical and equitable AI ensures that VBD control strategies consider gender-specific vulnerabilities.	[119]
6. **Clean water and sanitation** Ensure availability and sustainable management of water and sanitation for all	AI technologies have been used to identify water-related breeding sites for disease vectors. Using this information in underserved areas to inform sanitation and water security interventions can work towards SDG 6.	[120, 121]
7. **Affordable and clean energy** Ensure access to affordable, reliable, sustainable and modern energy for all	Considering the ecological footprint of AI and promoting energy-efficient systems supports sustainable infrastructure in low-resource settings.	[122]
8. **Decent work and economic growth** Promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all	As with SDG 1, reducing VBD burden by using AI-assisted disease control can reduce economic losses due to illness and support more productive communities.	[113]
9. **Industry, innovation and infrastructure** Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation	Promoting equitable use of AI supports the promotion of inclusive industrialisation by ensuring technological advancements benefit all communities.	[123]
10. **Reduce inequalities** Reduce inequality within and among countries	By addressing bias in training data and ensuring inclusive model design, ethical and equitable use of AI can avoid reinforcing existing health inequalities and works towards fair access to VBD control tools and data-driven health services.	[124]
11. **Sustainable cities and communities** Make cities and human settlements inclusive, safe, resilient and sustainable	Improving public health through VBD control in urban areas, ensuring gender- and culture-specific vulnerabilities are considered, and building security protocols and ethical safeguards, all supports work towards inclusive, safe, and resilient cities.	[125–127]
12. **Responsible consumption and production** Ensure sustainable consumption and production patterns	Incorporating AI in technological advances through an ethical lens encourages responsible use and sustainable development.	[123, 128]
13. **Climate action** Take urgent action to combat climate change and its impacts	Encouraging the environmentally-friendly use of AI in VBD control enables AI to be used to predict climatic drivers of the diseases and prepare for climate-driven health risks, whilst minimising its contribution to further climate change.	[10, 122]
14. **Life below water** Conserve and sustainably use the oceans, seas and marine resources for sustainable development	Similar to SDG 13, ethically-minded AI use encourages awareness of the water footprint of data centres, promoting sustainable water use, as well as the consideration of marine life in AI systems.	[122]
15. **Life on land** Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss	Ethical and equitable AI use in VBD control promotes biodiversity-conscious approaches, minimising ecological disruption.	[122, 129]
16. **Peace, justice and strong institutions** Promote peaceful and inclusive societies for sustainable development, provide access to justice for all and build effective, accountable and inclusive institutions at all levels	Putting transparency and accountability at the forefront of AI systems can foster public trust in VBD control programmes. Further, tailoring healthcare systems to local contexts and population differences enhances institutional responsiveness and inclusivity.	[127, 128, 130, 131]
17. **Partnerships for the goals** Strengthen the means of implementation and revitalize the global partnership for sustainable development	Using AI ethically and equitably catalyses collaboration across science, policy, industry, and society.	[38, 123, 132]

10 Concluding remarks

Artificial intelligence has the potential to reshape how we approach VBD management, offering new tools for prediction, surveillance, and control. However, as novel technologies are developed and existing ones are embedded into public health systems, it is critical we tackle the ethical and equity challenges they pose, including data gaps, algorithmic bias, the digital divide, and environmental sustainability. Here, we advocate for transparent, inclusive, and responsible AI use in VBD management. As AI technologies continue to evolve, so must our commitment to using it responsibly, with the well-being of both people and the planet at the forefront.

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Declarations

Conflict of interest The authors declare no competing interests.

Ethical approval Ethical approval was not required as the study did not involve human participants or animals.

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