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Perspective on ethical AI in computational epidemiology and one health with COHRCIE framework and computational prophylaxis

Ayomikun A. Awoseyi[1*], Ernest E. Onuiri[1], Ayodeji O. Olarinmoye[2], Adewale U. Oguntola[3] and Oluwawemimo O. Adebowale[4]

*Correspondence:
Ayomikun A. Awoseyi
awoseyiayomikun@gmail.com
[1]Department of Computer Science, Babcock University, Ilishan-Remo, Nigeria
[2]Department of Agriculture and Industrial Technology, Babcock University, Ilishan-Remo, Nigeria
[3]Department of Computer Sciences, Ajimobi Technical University (First Technical University), Abiola, Ibadan, Nigeria
[4]Department of Veterinary Public Health and Preventive Medicine, Federal University of Agriculture, Abeokuta, Nigeria

Abstract
The increasing use of artificial intelligence (AI) in Computational Epidemiology and One Health (CEOH) raises complex ethical challenges related to transparency, fairness, privacy, and legal compliance. This study examines the integration of computational science with traditional epidemiology to address health issues affecting humans, animals, and the environment. We trace the evolution of computational epidemiology and explore how machine learning and AI are applied in predictive modeling, disease surveillance, personalized medicine, resource allocation, and environmental monitoring. As AI transforms the landscape of CEOH, new ethical concerns continue to emerge. To address these concerns, we introduce the concept of computational prophylaxis, which enhances traditional disease prevention, and AI as a computational prophylactic tool. We also propose the COHRCIE framework, an ethical roadmap designed to ensure accuracy, transparency, integrity, privacy, equitable access, and responsible data governance in AI-driven CEOH initiatives. By promoting anticipatory ethics and embedding compliance throughout the AI lifecycle, COHRCIE provides a practical structure for building trustworthy, inclusive, and transparent AI systems in both research and applied health settings.

Keywords Computational epidemiology, One health, Computational prophylaxis, Artificial intelligence, Ethical framework

1 Introduction

Computational Epidemiology and One Health (CEOH) is an emerging field that seeks to apply models, algorithms and techniques from computational sciences such as mathematics, statistics, geoinformatics, computer science to the study of epidemics and One Health-related areas [1]. Although "computational epidemiology and One Health" is a relatively recent term, the practice of applying some computational techniques to traditional epidemiology has been around for a long time. Epidemiology is the branch of public health and medical sciences that investigates factors, distribution, control of diseases, and health related events in populations [2, 3]. As CEOH rapidly evolves, particularly with the integration of artificial intelligence (AI), there remains a notable lack of tailored ethical frameworks to guide its responsible development and application in interdisciplinary health research. Addressing this gap is essential to ensuring that technological advances align with public health values and ethical standards.

Ethics, as a branch of philosophy, explores the ethical principles of moral rightness and wrongness, examining moral concepts, judgments, and values [4]. Applied ethics brings these principles into real-world contexts including professional, public, and private domains. Many scientific disciplines have adapted applied ethics to their professional domains; the field of CEOH must now do the same. This need becomes particularly necessary as artificial intelligence (AI) and machine learning (ML) increasingly influence epidemiological modeling, disease prediction, and health decision-making.

According to Salathé (2018) [5], the objectives of digital epidemiology remain the same as traditional epidemiology. By extension, CEOH inherits these objectives, expanding them beyond the human domain to encompass animals, ecosystems, and environmental health through the One Health paradigm.

This perspective proposes an ethical framework for AI integration in CEOH, with a focus on two key contributions. First, it introduces the concept of computational prophylaxis, defined as the use of computational methods for proactive disease prevention. Second, it presents the COHRCIE framework: a structured ethical guide designed to support AI-driven research and practice in CEOH.

2 Computational epidemiology and one health (CEOH)

2.1 Evolution of computational epidemiology

The foundations of Computational Epidemiology and One Health (CEOH) date back to the 18th century, when Daniel Bernoulli applied mathematical analysis to disease dynamics. In 1760, to assess the impact of smallpox inoculation on population survival, Bernoulli developed the earliest form of mathematical compartmental models, the susceptible-infectious (SI) model [6, 7]. This pioneering work laid the groundwork for the use of mathematical modeling in disease prediction and control, and ultimately for the integration of such models into the broader CEOH framework. The key subfields of CEOH include mathematical epidemiology, computer science and related-field epidemiology, and geoinformatics epidemiology, amongst others.

Mathematical epidemiology relies on mathematical theories and models, with ordinary differential equations (ODEs), often referred to as compartment models, forming its cornerstone. A significant advancement occurred in 1927, when Kermack and McKendrick introduced the SIR (Susceptible, Infectious, Recovered) model [8]. Building on Bernoulli's SI framework, the SIR model provided a robust tool for simulating disease spread within populations, becoming a foundational framework for epidemic studies.

With the advent of advanced computing and data availability in the 20th and 21st centuries, computer science and related fields transformed epidemiology. This subfield draws on disciplines such as software engineering, bioinformatics, and computational biology, employing diverse techniques. These include formal methods (e.g., petri nets, cellular automata, graph theory), modeling and simulation (e.g., agent-based models, network theory), and artificial intelligence approaches (e.g., machine learning, computational intelligence). For instance, AI enables outbreak prediction by identifying patterns in large health datasets, while agent-based models simulate individual behaviors to predict disease spread.

Emerging technologies like the Internet of Things (IoT) have further enhance real-time data collection and monitoring. These advances in computational techniques, particularly the application of AI, are central to CEOH enabling a deeper understanding of the complex interactions among human, animal, and environmental health domains.

2.2 Machine learning and AI as a CEOH tool

Arthur Samuel is credited with coining the term *machine learning* (ML), which he defines it as a field of study gives computers or computing systems the ability to learn a particular task(s) without being explicitly programmed for it [9, 10]. It achieves this ability by leveraging on the patterns and information hidden in a data [11]. ML is commonly categorized based on the type of learning process: supervised, unsupervised, semi-supervised, reinforcement learning, self-supervised learning, and transfer learning.

Artificial intelligence (AI) is a broader domain that encompasses machine learning and includes technologies and methods aimed at replicating human-like cognitive and problem-solving abilities. Artificial intelligence can be classified based on capability: narrow AI (weak AI), general AI (strong AI), superintelligent AI and functionality: Reactive machine, limited memory, self-aware AI [12]. AI has become an essential tool in medical and public health applications, particularly in the fields of epidemiology and One Health. These technologies enable the processing and analysis of large volumes of health and disease-related data, which is critical for managing, preventing, and monitoring epidemiological events. In CEOH, AI and ML serve several key roles:

First, *predictive Modelling and disease forecasting* is one of the most prominent uses of AI in CEOH. Algorithms such as regression models, ML-based time series models, decision trees, and neural networks have been applied to forecast disease outbreaks and understand their dynamics [10]13]– [18]. These tools assist public health authorities in preparing for and mitigating the impact of epidemics.

Second, AI supports s*urveillance and early detection* of disease outbreaks. Continuous and autonomous monitoring is the hallmarks of disease surveillance; this is enhanced by AI methods that can detect patterns signaling emerging health threats. Several studies have demonstrated the use of these technologies in real-time surveillance and early warning systems [19–25].

Third, *personalized medicine and treatment* benefit from AI by shifting healthcare toward precision approaches. Genetic markers vary among individuals and populations, influencing how people respond to infections and treatments. AI has facilitated genomic analysis, accelerated drug discovery, and improved treatment efficacy by tailoring therapies to the specific genetic and physiological profiles of patients [26–30].

Fourth, *resource allocation and management* are increasingly informed by AI. Predictive algorithms help identify healthcare demand trends, optimize logistics, and guide equitable distribution of medical resources. AI techniques are also used to identify high-risk zones ("hotspots") and predict supply chain bottlenecks [31–33].

AI supports *environmental and zoonotic disease monitoring* a critical component of the One Health framework. ML and AI have been used to monitor zoonotic disease transmission, detect climate-related health risks, and assess the impact of land-use and ecological changes on disease emergence. These applications reflect the holistic, multispecies perspective of CEOH [34–38].

As AI and machine learning increasingly support disease prediction, resource allocation, and environmental monitoring, they amplify traditional public health practices. This leads us to the idea of computational prophylaxis: a term we use to describe the use of advanced computational tools to strengthen and extend classical prophylactic strategies.

3 Concept of computational prophylaxis

3.1 Definition and importance

Prophylaxis traditionally encompasses strategies to prevent disease onset or spread, most commonly categorized as biosecurity (measures to block pathogen entry and transmission in human, animal, or plant populations), medical (vaccinations, prophylactic medications), and sanitary (hygiene practices, water-and-food safety) [39–41]. While these approaches operate at physical and clinical levels, computational prophylaxis introduces a complementary, digital layer: it leverages computational methods, models, algorithms, and data-driven technologies to strengthen and optimize traditional prevention measures.

Computational prophylaxis supports biosecurity by predicting likely pathogen incursions through spatio-temporal risk models, enabling authorities to pre-position resources before outbreaks occur. In medical prophylaxis, it can personalize vaccine strategies or drug-distribution plans via machine-learning algorithms that identify high-risk subpopulations. For sanitary prophylaxis, computational tools can analyze real-time hygiene compliance data or model water-safety interventions under varied environmental scenarios.

Definition *Computational prophylaxis* (new term) is the application of computational science techniques such as predictive modeling, artificial intelligence, network analysis, and real-time data integration; to enhance the planning, implementation, and evaluation of established prophylactic strategies for infectious disease prevention, control, and surveillance.

By adding this digital dimension, computational prophylaxis does not replace traditional measures but amplifies their effectiveness, agility, and precision; unlike the three traditional categories, it relies on data analytics and algorithmic forecasting to anticipate and prevent outbreaks in real time. This integration is increasingly vital in epidemiology and One Health contexts, where complex interactions among humans, animals, and environments demand a proactive, data-driven form of prevention that merits its own prophylactic category.

3.2 Proactive disease surveillance and prevention strategies

Computational prophylaxis underpins proactive disease surveillance by integrating real-time health and environmental data, applying advanced analytics and AI to detect early signals of emerging threats. These systems support early warning, resource allocation, and targeted public health interventions, enabling timely, data-driven responses to prevent and contain outbreaks.

4 Ethical framework for AI-Driven CEOH

4.1 Traditional ethical theories foundation for ethics in CEOH

Applied ethics in computational epidemiology and One Health integrates three domains: philosophical ethics, computational science, and epidemiological and One Health see Fig. 1. Four foundational ethical traditions provide the theoretical basis for ethical AI in CEOH [42]:

4.1.1 Consequentialism (Utilitarianism)

Consequentialism is an ethical theory that evaluates the morality of actions based on their outcomes or consequences. A common form is utilitarianism, which promotes actions that maximize overall well-being or minimize harm [43]. In the context of AI in CEOH, consequentialist reasoning supports the development of tools that optimize health outcomes; such as models that prevent more infections or deaths, even if some individual trade-offs are involved. This guides calibration and deployment strategies for predictive models, focusing on maximizing lives saved, establishing effective interventions that minimizes infection rate, and minimizing harm through efficient outbreak response.

4.1.2 Deontological ethics

Deontology is an ethical framework that judges actions based on adherence to rules, duties, or rights, rather than consequences. Rooted in the work of Immanuel Kant, it

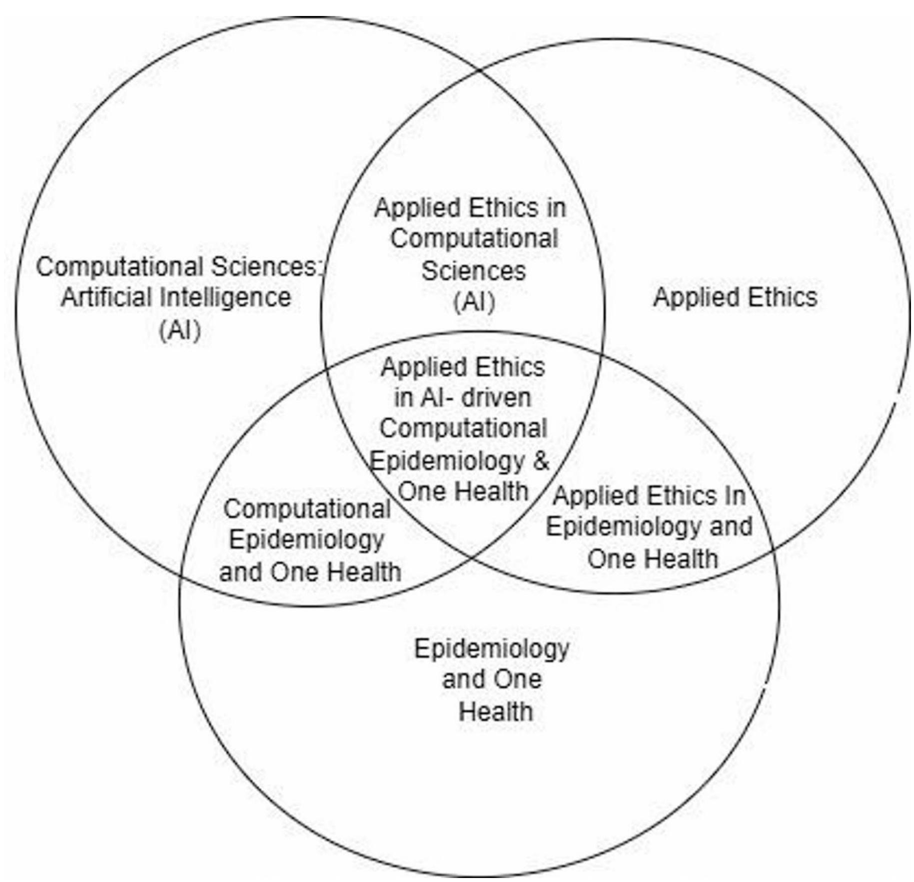

Fig. 1 Overlapping Domains Shaping Ethical AI in Computational Epidemiology and One Health

emphasizes principles like honesty, autonomy, and informed consent [42]. Applied to AI-driven CEOH, deontological ethics highlights the need to respect individual rights such as privacy and the right to understand how one's data is used, even when an algorithm could produce beneficial outcomes. It underpins requirements for explainability, fairness, and consent in data collection and model design.

4.1.3 Principlism

Principlism is a practical ethical framework commonly used in biomedical ethics, developed by Beauchamp and Childress. It is built around four principles: *autonomy* (respecting individuals' self-determination), *beneficence* (doing good), *non-maleficence* (avoiding harm), and *justice* (ensuring fairness and equity) [44]. In CEOH, principlism provides a balanced way to evaluate AI interventions: ensuring people are informed and protected (autonomy, non-maleficence), ensuring interventions benefit populations (beneficence), and ensuring fairness in AI access and outcomes (justice).

4.1.4 Relational and solidarity ethics

Relational ethics focuses on the ethical significance of relationships and interdependence between people, communities, and non-human life. Solidarity ethics extends this to include shared responsibilities and mutual aid, particularly across groups with unequal power or risk. Relational and solidarity ethics prioritizes empathy and interconnectedness over abstract rules or outcomes [42, 45]. These theories are especially relevant in One Health, which recognizes the health links among humans, animals, and ecosystems. In this context, AI tools should be co-designed with affected communities, reflect ecological interdependence, and support collective action across sectors.

Figure 1: Venn diagram illustrates how computational sciences, epidemiology and One Health; and Applied Ethics intersect.

Each ethical pillar of the proposed framework for AI-driven ethical computational epidemiology and One Health (ECEOH) can be traced back to one or more of these four foundational ethical theories.

4.2 Ethical pillars for AI-Driven ECEOH

4.2.1 Accuracy and reliability of AI insights

Theoretical Grounding:

- ***Consequentialism***: Seeks to maximize overall health benefits by minimizing false positives and false negatives, thereby reducing harm.
- ***Principlism***: Emphasizes the obligation to promote accurate outcomes and prevent harm arising from unreliable predictions.

Accurate and reliable AI models are critical in CEOH because errors can lead to misallocated resources, unnecessary alarm, or missed outbreaks. To ensure dependability, models must undergo a rigorous development process including validation on representative datasets and quantification of uncertainty. High-quality predictions foster stakeholder trust, support equitable resource allocation, and enable effective prevention protocols, reflecting both consequentialist and principlist commitments [44, 45].

4.2.2 Integrity and transparency of AI

Theoretical Grounding:

- ***Deontology***: Upholds the duty of honesty and respect for individuals' rights by demanding clear, explainable processes.
- ***Principlism (Autonomy)***: Supports informed decision-making by ensuring stakeholders understand how AI decisions are reached.

Transparent and reproducible AI practices are essential in CEOH to maintain public trust and allow independent verification [46]. Integrity requires that data sources, modeling choices, model development, and algorithmic assumptions are openly documented. Transparency mechanisms, such as shared code repositories, model cards, and interactive explainability tools, enable stakeholders to scrutinize AI insights, reproduce results, and hold developers accountable. In practice, these measures enhance accountability and empower communities and decision-makers to interpret model outputs responsibly. This pillar upholds ethical obligations to truthfulness and user autonomy, reducing the risk of hidden biases or undisclosed errors that could compromise public health responses.

4.2.3 Data governance and privacy

Theoretical Grounding:

- ***Principlism (Justice)***: Demands fair distribution of benefits and burdens, ensuring no group is disadvantaged.
- ***Relational and Solidarity Ethics***: Emphasizes mutual responsibility and collective well-being across human, animal, and environmental health actors.
- ***Consequentialism***: Protecting privacy reduces the risk of data breaches or misuse that could cause widespread harm, aligning with the goal of maximizing overall wellbeing.

In CEOH, handling sensitive health and environmental data demands robust privacy measures. Data collection should adhere to these principles: *data minimization* only gathering what is strictly necessary for the health objectives, and require informed, context-appropriate consent. Technical safeguards such as *anonymization*, *pseudonymization*, and *differential privacy techniques* help prevent re-identification. *Secure infrastructure* employing encryption at rest and in transit, role-based access controls, and regular security audits to guard against unauthorized access [43, 44, 46, 47].

By integrating these protections, computational epidemiologists honor individual autonomy, prevent potential harms from data misuse, and build the public trust essential for the successful adoption of AI tools in One Health initiatives.

4.2.4 Equitable access

Theoretical Grounding:

- ***Principlism (Justice)***: Requires fair distribution of benefits and burdens so that no group bears disproportionate risks or is denied AI-enabled health services.
- ***Relational and Solidarity Ethics***: Emphasizes collective responsibility and mutual support across human, animal, and environmental health domains, ensuring vulnerable populations are not left behind.

In CEOH, AI models and tools must be designed to address, rather than exacerbate, existing health inequities. This involves curating training data sets that represent diverse populations and ecological contexts, and embedding fairness constraints into algorithms to avoid discriminatory predictions. Resource allocation algorithms should incorporate equity metrics to guide distribution of vaccines, diagnostics, and surveillance capabilities to underserved communities. Deployment strategies must proactively prioritize regions at greatest risk such as remote or economically disadvantaged areas, and include mechanisms for ongoing feedback from affected stakeholders [42, 45, 48].

Medical resource-allocation solutions that rely on predictive models must also make explicit provisions for both current and future uncertainties by integrating scenario analyses or safety-margin buffers into distribution plans.

4.2.5 Stakeholder engagement

Theoretical Grounding:

- ***Relational Ethics***: Emphasizes the moral significance of relationships, interdependence, and dialogue among all parties affected by AI-driven interventions.
- ***Solidarity Ethics***: Calls for collective responsibility and inclusivity, ensuring that AI tools are co-developed with and benefit diverse stakeholder groups.
- ***Deontological Ethics***: Imposes a duty to include all affected parties, respecting their rights to be consulted on decisions that impact them.

In CEOH, meaningful stakeholder engagement entails involving those who generate data, govern systems, and live with AI decisions, public health officials, veterinarians, environmental scientists, community representatives, and frontline workers, at every stage of the AI lifecycle [49]. This can take the form of interdisciplinary advisory boards that shape research questions, participatory design workshops that uncover local needs and ethical concerns with continuous feedback mechanisms [50, 51]. By honoring these ethical duties, computational epidemiologists build AI solutions that are trustworthy, culturally appropriate, and aligned with real-world priorities.

4.2.6 Principle of solidarity

- ***Solidarity Ethics***: Underlines shared responsibilities and mutual support across human, animal, and environmental health, emphasizing collective action for common good.
- ***Relational Ethics***: Highlights the interconnectedness of all stakeholders and the importance of standing with and for those impacted by AI interventions.

In CEOH, the principle of solidarity calls computational epidemiologists to “stand alongside” communities and ecosystems affected by disease dynamics. This involves prioritizing collaborative partnerships, knowledge sharing, and capacity building such as co-creating surveillance tools with local health workers or sharing predictive insights with wildlife conservation organizations to inform ecosystem management. By embedding solidarity into project design, practitioners foster resilience, ensure that benefits are distributed equitably, and uphold an ethic of care that spans populations and species [42, 44, 52]. It extends beyond individual projects, encouraging networks of researchers, policymakers, and practitioners to support each other through collaborations and open-data policies, joint training programs, and transboundary emergency response and alliances. Solidarity thus transforms CEOH from isolated interventions into a collective movement for planetary health.

4.2.7 Education and training

Theoretical Grounding:

- ***Deontological Ethics***: Emphasizes the duty of competence, requiring practitioners to acquire and maintain the skills needed for ethical AI practice.
- ***Principlism (Non-maleficence*, *Beneficence)***: Ensures that those using AI tools do so safely and effectively to maximize benefits and minimize harm.
- ***Relational Ethics***: Supports shared learning and capacity building among diverse stakeholders, fostering mutual respect and collective growth.

In CEOH, robust education and training programs are essential to prepare researchers, public health professionals, veterinarians, and community partners for the ethical development and use of AI tools. Curricula should cover core topics such as algorithmic bias, data privacy, transparency practices, and participatory design methods [42, 50, 51, 53, 54]. The CEOH community owes a deontological duty to competence and collaborative development, promotes fair and accurate AI application, and builds a culture of shared responsibility.

4.2.8 Monitoring and evaluation

- ***Consequentialism***: Focuses on tracking outcomes to ensure AI interventions continue to deliver net benefits and reduce harm over time.
- ***Principlism (Non-maleficence)***: Emphasizes ongoing assessment to identify and mitigate unintended negative consequences.
- ***Deontological Ethics***: Imposes a duty of care to monitor AI systems' performance and intervene when ethical standards are at risk.

Continuous monitoring and evaluation are vital in CEOH solutions, to detect model drift, emerging biases, changes in population need, or adverse impacts that may arise after deployment. Implementation of performance dashboards that track and report key performance metrics, conducting periodic ethical audits, and establishing feedback channels for users and communities to report concerns. Evaluation should also assess real-world outcomes, such as the effectiveness of AI-informed interventions in reducing disease incidence or improving resource distribution [55, 56].

By embedding systematic monitoring and evaluation into AI workflows, computational epidemiologists uphold their duty to prevent harm, ensure accountability, improve public trust by adaptively refine models and policies.

5 Building the ethical framework in AI-driven CEOH

Integrating core ethical principles into AI-driven Computational Epidemiology and One Health (CEOH) is essential to ensure these powerful tools advance public welfare. A cohesive ethics framework must preserve fairness, transparency, accountability, and respect for autonomy across both research and application contexts. Harmonizing these principles into a unified ethical structure promotes trust, consistency of practice, and clarity for all stakeholders.

To translate these principles into practice, the proposed framework must pursue two complementary objectives:

i). Define framework's core ethical values (fairness, transparency, accountability, privacy, beneficence, non-maleficence) and embed them in clear, actionable guidelines for all participants.

ii). Integrate ethical guidelines and standards into a unified policy framework that governs all AI-driven CEOH initiatives.

These two objectives provide the scaffolding for proposed Computational One Health Research Compliance and Integrated Ethics (COHRCIE) framework.

6 Computational one health research compliance and integrated ethics (COHRCIE) framework

The Computational One Health Research Compliance and Integrated Ethics (COHRCIE: pronounced "Core-see") framework translates the ethical pillars of Sect. 4 into actionable guidance for both research and operational settings. COHRCIE-1.0 comprises six core components: *Ethical Consideriation*, *Stakeholder Engagement*, *Education and Training*, *Monitoring and Evaluation*, *Data Governance*, and *Legal Compliance* refer to Table 1. To address the distinct demands of academic inquiry versus real-world deployment, COHRCIE is organized into two parallel tracks: *COHRCIE-Research* and *COHRCIE-Application*.

6.1 COHRCIE-RESEARCH V1.0

AI-driven research in Computational Epidemiology and One Health (CEOH) offers unprecedented insights into disease dynamics, but also raises ethical challenges around data use, model validity, and community impact. The COHRCIE-Research track provides a six-component classified as either essential, relevant or optional, roadmap to ensure that scholarly work remains both innovative and ethically sound, see Table 2.

All scenarios below are hypothetical and serve to exemplify potential ethical questions COHRCIE-Research can solve in AI-driven CEOH studies.

Table 1 COHRCIE framework components and illustrative application

No	Component	Description	Example
1	Ethical Consideration (EC)	Embeds fairness, transparency, accountability, and privacy.	Publishing "model cards" alongside AI model.
2	Data Governance (DG)	Ensures data quality, anonymization, secure storage, and responsible use.	Implementing data minimization, anonymization and privacy.
3	Stakeholder Engagement (SE)	Involves all affected parties throughout development and deployment.	Co-designing tools with health workers and community representatives.
4	Education and Training (ET)	Prepares users to interpret, trust, and apply AI tools responsibly.	Delivering workshops and tutorials for end-users and policymakers.
5	Monitoring and Evaluation (ME)	Tracks model performance, bias, and ethical risks over time.	Conducting periodic audits and update models based on field reports.
6	Legal Compliance (LC)	Aligns AI tools with laws, regulations, and ethics review processes.	Demonstrating adherence to local and international health laws.

Table 2 Summary of COHRCIE-Research framework V1

No	Component	Summary	Relevance
1	Ethical Consideration (EC)	Embed fairness, transparency, accountability, and privacy by default in model design and reporting	Essential
2	Data Governance (DG)	Enforce data minimization, quality checks, secure storage, access controls, and audit logging.	Essential
3	Stakeholders Engagement (SE)	Co-design protocols with communities, health officials, and veterinarians; ensure cultural fit and trust. Identifying funders and special interest groups.	Relevant
4	Education and Training (ET)	Develop and document training plans and competency assessments for research teams and operational users.	Optional
5	Monitoring and Evaluation (ME)	Reproducibility checks, bias audits, and impact assessments, maintaining a transparent post publication audit trail.	Optional
6	Legal Compliance (LC)	Document IRB approvals, consent procedures, and data-protection compliance when regulated data apply.	Relevant

6.1.1 Ethical consideration (EC)

Ethical Consideration ensures that fairness, transparency, accountability, and privacy are built into AI model design from the outset.

Scenario 1 Equitable Vaccine Resource Allocation Based on Predictive Modeling.
A multidisciplinary team develops an AI model to help public health agencies in a West African country predict Foot and Mouth Disease hotspots and plan equitable vaccine distribution. They produce risk-ranking maps and distribution schedules. The following questions arise:

- Were modeling choices, trade-offs, and risks clearly documented?
- Was fairness evaluated across all affected groups, especially underrepresented ones?

COHRCIE-Research prompts researchers to go beyond performance metrics. Ethical consideration requires documenting model assumptions, clarifying intended use, assessing population fairness, and ensuring safeguards are explicitly addressed in publications.

6.1.2 Data governance (DG)

Data Governance in research ensures that data collection, management, and sharing uphold principles of privacy, quality, security, and transparency.

Scenario 2 Integrated Outbreak and Mobility Data for Forecasting Rift Valley Fever.
A research team seeks to model Rift Valley Fever transmission corridors in East Africa by integrating anonymized mobile phone data, livestock trade records, and outbreak alerts. While the model shows strong predictive ability, ethical concerns surface around the handling of sensitive human mobility data, inconsistencies in livestock reporting formats, and the lack of a clear access protocol for shared datasets:

- Were data collection practices guided by minimization and consent?
- How were privacy risks mitigated, especially in mobility datasets?
- Were access controls and audit trails established to ensure responsible data use?

COHRCIE-Research reinforces that ethical research requires more than innovative analytics. It demands transparent, secure, and equitable data governance. Researchers must document their data sourcing, quality control measures, access policies, and ethical safeguards to ensure compliance with institutional review board (IRB) requirements and to encourage reproducibility.

6.1.3 Stakeholders engagement (SE)

Stakeholder Engagement ensures that AI research in CEOH reflects community needs, respects cultural contexts, and incorporates perspectives from all affected parties.

Scenario 3 Mapping Environmental Risk Factors for Avian Influenza.
A multi-disciplinary team launches an AI study to map environmental risk factors for avian influenza along an Asian country's migratory bird flyways. The study was timely and scientifically promising. However, these ethical questions were left unanswered or only partially addressed in their publication.

- Were all relevant stakeholders, including local communities, adequately identified and consulted?
- Were consent materials available in appropriate languages and culturally appropriate formats?
- Were governance and data-sharing agreements established to protect community interests?

COHRCIE-Research insists that stakeholder engagement must be inclusive. Ethical research requires, culturally grounded communication, and participatory governance that elevates the voices of those most affected by both the process and outcomes.

6.1.4 Education and training (ET)

Education and Training equip both researchers and end-users with the competencies required to develop, interpret, and responsibly apply AI tools in CEOH research settings. While ET is optional for purely academic projects, it becomes essential when research is intended for operational deployment.

Scenario 4 Predictive Vaccine Distribution System for Public Health Management.
A research consortium publishes a paper on a machine learning model designed to forecast measles vaccine demand at district level across a Southeast Asian country.

- Was training needs for non-technical users identified and addressed in the study design?
- Was training materials or formats made available for capacity building and sustained use?

COHRCIE-Research emphasizes that preparing end-users is part of ethical responsibility. When research outputs are intended for real-world application, authors must document training strategies that enable correct interpretation, safe use, and equitable access to the benefits of AI.

6.1.5 Monitoring and evaluation (ME)

Monitoring and Evaluation ensure that AI models used in CEOH research remain reliable, fair, and relevant over time through systematic performance and impact assessments.

Scenario 5 Post-Publication Audit in Disease Forecasting.

A research team publishes an AI model predicting dengue hotspots in an European country. A year later, an independent group attempts to reproduce the results using the shared code and data. They discovered declining accuracy, and missing model development process, undetected bias. The following questions arise:

- Were reproducibility protocols and documentation made available for post-publication validation?
- Was any plan included for ongoing model evaluation or version updates?
- How were emerging biases or shifts in data patterns intended to be addressed?

COHRCIE-Research maintains that ethical AI research includes transparency beyond the moment of publication. Authors must support reproducibility, plan for long-term evaluation, and establish feedback loops.

6.1.6 Legal compliance (LC)

Legal Compliance ensures that AI research involving regulated data adheres to applicable laws, ethical approvals, and institutional requirements for the protection of people, animals, and ecosystems.

Scenario 6 AI Model for Predicting Influenza Spread.

A research team publishes a paper on an AI model predicting seasonal influenza spread using anonymized patient records from Hospital X. Their methods section describes data sources and modeling steps but omits any legal details. The following questions arise.

- Were data usage and model deployment in compliance with local and international privacy regulations?
- Was informed consent obtained or formally waived through an institutional ethics process?
- Were legal risks or obligations identified and transparently addressed in the publication?

COHRCIE-Research affirms that legal compliance is a core ethical responsibility in AI research. Studies must document consent procedures, institutional approvals, and data protection measures to uphold public trust and meet legal standards.

By embedding the *Ethical Consideration*, *Stakeholder Engagement*, *Monitoring & Evaluation*, and *Data Governance* into manuscript preparation process, COHRCIE-Research empowers authors to avoid ethical blind spots; ensures models remain reproducible, fair, and transparent; and bridge the gap between academic insight and actionable public-health impact.

6.2 COHRCIE-APPLICATION V1.0

AI-driven epidemiological and One Health systems or solutions developed as applications have more direct ethical impact on stakeholders. These applications when used could have consequential effects on its users. An AI tools wrongly identifying an outbreak of an infectious disease would be catastrophic. Hence, stricter ethical rules must

Table 3 Summary of COHRCIE-Application framework V1

No	Component	Summary	Relevance
1	Ethical Consideration (EC)	Ensure transparency, accountability, and fairness are embedded in system logic and deployment plans.	Essential
2	Data Governance (DG)	Maintain data integrity, minimize risks, define access roles, and align with privacy standards.	Essential
3	Stakeholders Engagement (SE)	Involve communities, practitioners, and policymakers throughout system design, deployment, and feedback.	Relevant
4	Education and Training (ET)	Develop user-friendly training programs and guidance to promote safe and effective AI use	Essential
5	Monitoring and Evaluation (ME)	Plan for post-deployment auditing, feedback loops, and ethical risk detection	Essential
6	Legal Compliance (LC)	Secure approvals, define liability, and comply with regulatory and consent frameworks	Essential

be enforced through the COHRCIE-Application ethical framework. We identify as essential all six components of the COHRCIE-Application framework, see Table 3.

6.2.1 Ethical consideration (EC)

In real-world deployments, ethical considerations must be actively built into AI system design, deployment protocols, and public communication strategies.

Scenario:

A national health agency launches an AI-driven alert system to detect potential outbreaks based on hospital reports and animal health data. The system begins issuing high-risk classifications for certain rural districts, triggering travel bans and emergency funding shifts.

- Was the model's purpose, decision logic, and risk thresholds made transparent to all users?
- Were affected populations informed and involved before the system went live?

COHRCIE-Application requires that AI solutions not only perform well, but also accountable. Ethical deployment demands clear documentation, explainable outputs, public transparency, and built-in procedures to identify and correct harm.

6.2.2 Data governance (DG)

In application settings, data governance protects user privacy, ensures data quality, and supports ethical decision-making throughout the AI system's lifecycle.

Scenario:

A national platform for zoonotic disease surveillance integrates human clinic data, veterinary records, and satellite feeds to forecast outbreak risks. While the AI backend functions efficiently, inconsistent data quality, unclear access controls, and a lack of privacy safeguards raise legal and ethical concerns.

- Were data minimization and anonymization protocols implemented before deployment?
- How is data integrity maintained across heterogeneous sources?
- Are access rights, user roles, and data-sharing clearly defined and enforceable?

COHRCIE-Application insists that data governance is a frontline safeguard. AI tools must be supported by clear protocols for data quality, protection, access control, and regulatory compliance to preserve trust and legitimacy.

6.2.3 Stakeholder engagement (SE)

In deployment contexts, stakeholder engagement ensures AI tools reflect the priorities, capacities, and lived realities of those affected by their outputs.

Scenario:

An international NGO rolls out an AI-powered alert system for zoonotic spillovers in a rural region. Though technically sound, the app receives low adoption among livestock farmers and is distrusted by local veterinary officers.

- Were all relevant stakeholders involved from the start?
- Were communication methods adapted to local languages and knowledge systems?
- Did deployment include channels for feedback, trust-building, and shared ownership?

COHRCIE-Application affirms that ethical deployment requires co-creation, not just consultation. Stakeholders must be engaged throughout the AI lifecycle to ensure legitimacy, usability, and context-aligned impact.

6.2.4 Education and training (ET)

In real-world deployment, education and training are critical to ensure that AI tools are interpreted accurately, used safely, and integrated into local decision workflows.

Scenario:

A health ministry introduces an AI-based dashboard to forecast vaccine demand across provinces. Although the tool is functional, health workers misinterpret the dashboard's forecasts and default to older manual allocation routines.

- Were users trained to understand, interpret, and act on the AI system's recommendations?
- Were training materials designed for different user groups with varied technical skills?
- How is user competence supported after deployment?

COHRCIE-Application emphasizes minimizing ethical risks. Deploying AI solutions responsibly requires accessible training programs, tailored resources, and continuous user support to prevent misuse and promote effective outcomes.

6.2.5 Monitoring and evaluation (ME)

In deployment settings, continuous monitoring and evaluation are essential to detect performance drift, mitigate emerging harms, and adapt AI tools to changing realities.

Scenario:

A deployed AI model forecasts dengue outbreaks and informs vector control across several municipalities. Initially effective, the model begins to underperform following climate shifts and changes in reporting behavior.

- Was a plan established for ongoing monitoring of model performance and fairness?
- Are there mechanisms to identify and respond to model drift or changing conditions?

- Is there a structured pathway for user feedback and ethical issue reporting?

COHRCIE-Application requires that AI tools be treated as dynamic systems. Ongoing evaluation, ethical auditing, and performance feedback loops are critical to ensuring continued reliability, safety, and public value.

6.2.6 Legal compliance (LC)

In applied settings, legal compliance ensures that AI tools operate within the bounds of data protection laws, regulatory approvals, and institutional accountability.

Scenario:

A national public health agency partners with a private technology firm to deploy an AI system for early tuberculosis screening using patient data from regional hospitals. The system is integrated into existing clinical workflows and generates risk scores that assist diagnostic decisions.

- Was the use of patient data authorized by institutional review boards or ethics committees?
- Were legal obligations for data sharing, storage, and cross-border transfer fully addressed?
- Were patients informed about the AI system, and is accountability clearly assigned between partners?

COHRCIE-Application stresses that legal readiness is integral to ethical deployment. Regulatory compliance, transparency in consent, and institutional accountability must be established before implementation to prevent legal conflicts and safeguard public trust.

By operationalizing the COHRCIE-Application components, developers and implementers can move beyond technical deployment to responsible integration. The framework highlights that ethical success in real-world AI systems requires not just functional accuracy, but also transparency, legal preparedness, participatory design, and sustained monitoring. COHRCIE-Application offers a practical roadmap to embed these safeguards across AI-supported One Health interventions, ensuring they are not only innovative but also socially and ethically viable.

7 Conclusion

The integration of AI into Computational Epidemiology and One Health (CEOH) is positioned in this paper as a form of computational prophylaxis that offers technical innovation while demanding ethical alignment. We respond to this need by proposing the COHRCIE framework, a dual-track model that embeds ethical and legal accountability into both research and application settings. Structured around six core components and grounded in applied ethical principles, the framework supports researchers and practitioners in developing AI tools that are not only effective, but also transparent, inclusive, and socially responsible.

Through scenario-based illustrations, we highlight ethical questions that may arise across both tracks of the framework. These examples demonstrate how proactive reflection on ethical consideration, data governance, stakeholder engagement, education and training, monitoring and evaluation, and legal compliance can reduce ethical risks and build public trust. Ethical excellence is not peripheral to scientific progress; it is essential to the credibility and legitimacy of AI in public health. As AI becomes increasingly integrated into health systems, the COHRCIE framework provides a timely and practical roadmap. It promotes a shift from reactive oversight to proactive design, helping to bridge the gap between academic development and real-world implementation of AI-enabled CEOH solutions.

8 Future work

Future work should focus on operationalizing the COHRCIE framework through practical tools such as ethical checklists, implementation guides, and audit protocols. Empirical validation through case studies in both research and applied contexts will be important for assessing its utility and adaptability. Collaboration with policymakers will help embed the framework into national and international One Health strategies. Finally, cross-cultural and cross-regulatory partnerships will be essential for refining the framework's applicability in diverse global settings.

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A.A.A. Conceptualization, methodology, original drafting.O.E.E. Supervision, validation.O.A.O. Supervision, critical review.O.A.U. Editing, drafting.A.O.Y. Validation, review. All authors reviewed and approved the manuscript.

Data availability
No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent to publish
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Human and animal rights
This study did not involve human participants or animal subjects.

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The authors declare no conflict of interest.

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