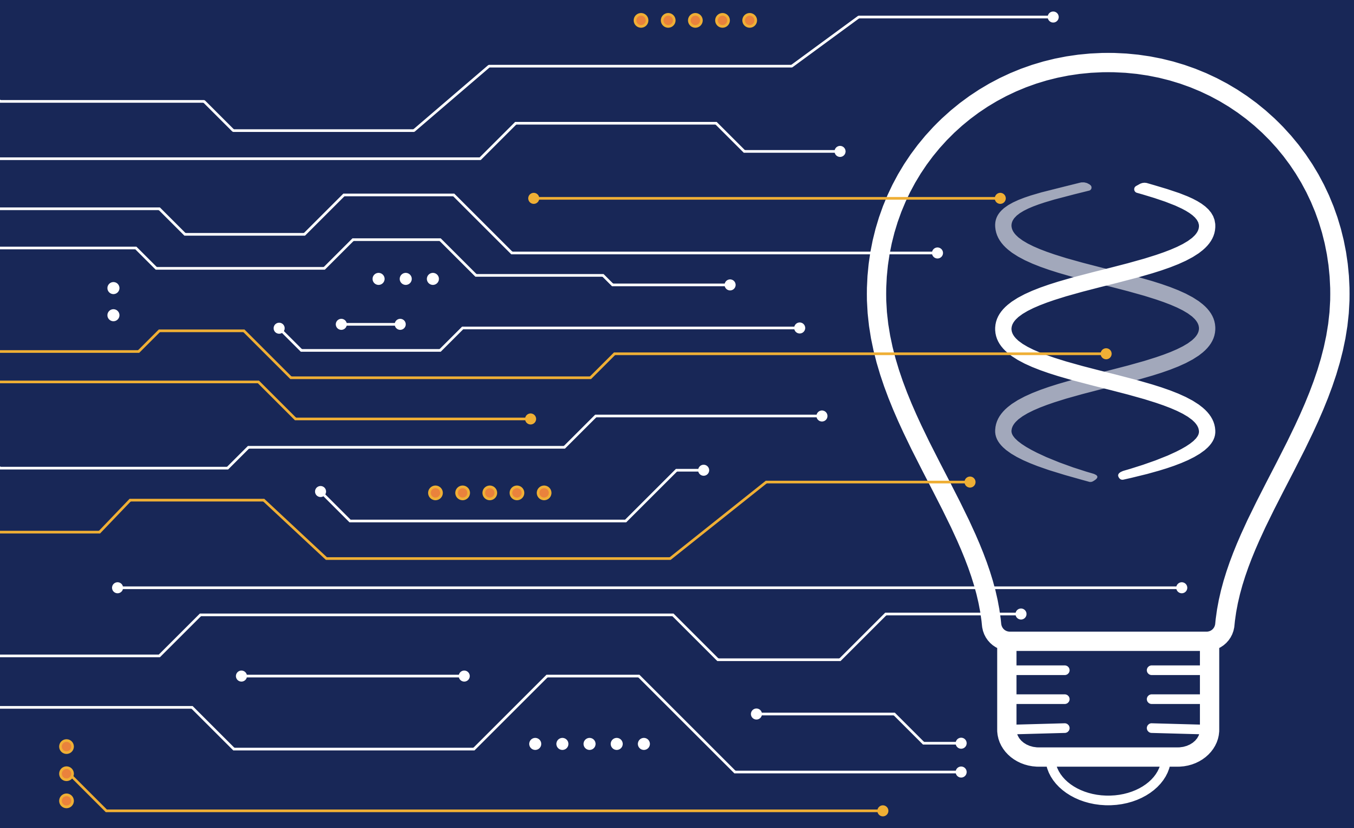
World Health Organization

Artificial intelligence and evidence-informed policy – emerging challenges and opportunities

Discussion paper



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Contents

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Methodology

This discussion paper was developed through a collaborative, multi-stage process. The Governance Lab at New York University, United States of America, was commissioned to conduct initial research and to prepare preliminary content. This was then reviewed and refined by a core development team from WHO's Department of Data, Digital Health, Analytics and Artificial Intelligence and the Department of Science for Health. An external Editorial Board comprising international experts in artificial intelligence and evidence-informed health policy provided guidance throughout the development process. The document underwent peer review by external experts with diverse experience across different regions and contexts, as well as internal review by WHO staff and consultants. This iterative, consultative approach aimed to ensure that the paper reflects diverse perspectives and expertise from the domains of both artificial intelligence and evidence-informed policy-making.

Glossary

1. Artificial intelligence (AI): A broad term referring to the capability of machines to perform intelligent tasks. It is a branch of computer science, statistics and engineering that utilizes algorithms or models to execute tasks and exhibit behaviours such as learning, decision-making and prediction *(1–3)*. Three broad types of AI techniques are: machine learning, logic- and knowledge-based approaches, and statistical methods *(2)*.
2. Deep learning: A subset of machine learning that is based on artificial neural networks or multi-layered models, which are used progressively to extract features from data *(1,3)*.
3. Generative AI: A category of AI techniques where machine learning models are trained on datasets to create new outputs such as text, images, videos and music. These models learn patterns and structures from their training data and then produce novel data based on the predictions they make from these learned patterns *(4)*.
4. Large language model (LLM): A type of generative AI that primarily receives text as input and provides responses that are also in text *(4)*.
5. Large multi-modal model (LMM): A type of generative AI capable of accepting various types of data inputs and generating diverse outputs that are not limited to the type of data originally fed into the algorithm *(4)*.
6. Logic- and knowledge-based approaches: A type of AI that performs tasks by applying logical rules to stored information. These techniques include organizing knowledge, learning rules from examples, drawing conclusions from facts, reasoning with symbols, and mimicking expert decision-making *(2)*.
7. Machine learning (ML): A subset of AI techniques that focuses on developing models and algorithms that learn patterns from data to solve specific tasks, rather than relying on predefined, explicit rules *(2,3)*.
8. Statistical approaches: A category of AI techniques that treat learning and decision-making as probabilistic modeling and inference *(5,6)*, including Bayesian estimation and search and optimization methods *(2)*.

Executive summary

Artificial intelligence (AI) is rapidly transforming the landscape of evidence-informed policy-making (EIP) for health. By enabling faster synthesis and analysis of diverse, large-scale data, AI promises to expand the evidence base available to policy-makers, enhance scenario modelling and simulation, and support adaptive and responsive decision-making. These capabilities can accelerate the development of policies, improve the effectiveness of implementation, and facilitate both continuous monitoring and refinement in complex and dynamic health contexts.

This paper synthesizes current knowledge and emerging insights on the application of AI across the EIP cycle, highlighting examples where AI has enhanced problem understanding, policy design, operational efficiency and impact assessment. The paper emphasizes that AI complements rather than replaces human judgement, underscoring the necessity for transparency, explainability and ethical oversight to maintain trust and accountability.

However, integrating AI into EIP also presents significant challenges, including risks of algorithmic opacity, bias amplification, equity concerns, data privacy issues, cybersecurity threats, resource demands and regulatory uncertainty. These risks span the entire policy life cycle and necessitate robust governance frameworks that blend the rigor, transparency and inclusiveness of traditional EIP with AI-specific life cycle monitoring, risk management and rights protection.

The World Health Organization's guidance on AI ethics and governance in health provides essential domain-specific principles, advocating for human autonomy, safety, equity and public interest as foundational guardrails. Governance approaches must be adaptable to diverse national contexts and evolving AI technologies in order to ensure that AI applications in policy-making are ethical, equitable, evidence-responsive and aligned with societal values.

Building on shared principles between AI and EIP governance, this paper outlines practical policy considerations, including adopting living evidence workflows, integrating AI outputs with expert judgement, embedding human oversight and fostering collective intelligence in decision-making. It calls for strengthened interdisciplinary collaboration and capacity-building as well as an inclusive approach to leverage AI's potential for advancing health policy. A summary table (Table 1) maps the opportunities, risks, governance insights, and practical responses discussed in Sections 4–7 across each phase of the policy cycle, offering a concise reference for policy-makers seeking to navigate the integration of AI into EIP.

By thoughtfully navigating opportunities and challenges, policy-makers and stakeholders can harness AI to strengthen evidence-informed policy-making, ultimately improving health outcomes and sustaining public trust in an increasingly data-driven world.

Table 1. Examples of opportunities, risks, governance insights and practical responses across the policy cycle

Policy phase	AI opportunities (Section 4)	Key risks (Section 5)	Governance insights (Section 6)	Practical responses (Section 7)
Cross-cutting (applies to all phases)	⇨ More comprehensive data integration ⇨ Research synthesis ⇨ Scenario modelling ⇨ Adaptive feedback across the cycle ⇨ Accelerate movement through policy cycle	⇨ Opacity and accountability ⇨ Power concentration and equity ⇨ Regulatory gaps ⇨ Erosion of human expertise ⇨ Bias and discrimination ⇨ Epistemic injustice and knowledge exclusion ⇨ Resource intensity	⇨ Transparent and auditable decision-making ⇨ Participatory engagement ⇨ Data governance and quality (FAIR principles) ⇨ Rights and accountability frameworks ⇨ Evidence standards and reporting ⇨ Risk-based regulation and life cycle oversight	⇨ Prioritize augmentation over automation ⇨ Human-in-the-loop governance ⇨ Combine AI with collective intelligence ⇨ Navigate evolving concepts of evidence ⇨ Link AI research to policy applications
Understanding the problem	⇨ Pattern detection and prediction ⇨ Enhanced situational awareness	⇨ Data bias and misrepresentation ⇨ Reinforcement of historical bias ⇨ Oversimplification of complex issues ⇨ Mis/disinformation	*See cross-cutting principles above*	⇨ Living evidence workflows ⇨ Multidisciplinary oversight ⇨ Context-specific question framing ⇨ Blend AI outputs with expert judgement
Designing the solution	⇨ Idea generation and option surfacing ⇨ Resource allocation optimization ⇨ Operational efficiency improvements	⇨ Over-optimization of measurable objectives ⇨ Algorithmic narrowness ⇨ Legitimacy risks ⇨ Ethical blind spots ⇨ Innovation constraints ⇨ Stakeholder exclusion	*See cross-cutting principles above*	⇨ Pilot projects and structured appraisals ⇨ Technology readiness assessments ⇨ Algorithmic impact assessments ⇨ Map tasks to comparative advantage
Achieving impact (Including implementation, monitoring & adjustment)	⇨ Adaptive policies and real-time feedback ⇨ Implementation dashboards ⇨ Public sentiment analysis ⇨ Iterative evidence-based decision-making ⇨ Learning from policy failures	⇨ Incentive distortions and system gaming ⇨ Cybersecurity threats to programme delivery ⇨ Adaptability challenges in novel contexts ⇨ Overemphasis on quantitative metrics ⇨ Causality and attribution gaps ⇨ Feedback loop risks ⇨ Privacy violations ⇨ Resistance to change and path dependency ⇨ Policy drift and inflexibility	*See cross-cutting principles above*	⇨ Bias-testing and auditing ⇨ Post-deployment audits ⇨ Real-time analytics for adjustments ⇨ Flexible governance and adaptive protocols ⇨ Systematic risk-mapping

Note: This table presents selected examples that are relevant to each phase. Cross-cutting risks affect all policy phases (Section 5.1), and governance insights and practical responses build on foundational principles that apply across the cycle. Several opportunities and responses may be relevant to multiple phases. For a comprehensive discussion, see sections 4–7.

1. Introduction

Policy-making that is grounded in robust evidence is vital for addressing complex public health policy challenges, achieving effective outcomes and fostering public trust. Evidence-informed policy-making (EIP) systematically applies research, data and practice-based insights to the design, implementation and evaluation of policy. Conventional methods, such as randomized controlled trials and systematic reviews, remain essential but their limitations and resource demands necessitate complementary approaches.

This paper examines how artificial intelligence (AI) can augment EIP across the policy cycle by accelerating the generation of evidence, enabling faster synthesis and expanding the analysis of large and diverse datasets. Used effectively, AI can expand the evidence base available to policy-makers and can support more timely, adaptive decisions while preserving human judgement and context.

Integrating AI into EIP also raises issues that must be addressed – including the transparency and explainability of systems, risks related to bias and equity, data protection, accountability and sustainability. This paper maps these opportunities and risks across the policy cycle (sections 4–5), examines how existing EIP and AI governance frameworks can be aligned to address the challenges (Section 6), and provides practical operational guidance for responsible implementation (Section 7).

2. Intended users

The primary audiences for this document are policy-makers, regulators, health managers and AI developers.

3. Evidence-informed policy-making

EIP is a systematic and transparent process that uses the best available evidence – including both research findings and contextual knowledge – to design, implement and refine public policy, ensuring relevance, equity and effectiveness across diverse settings. This approach builds on the legacy of evidence-based medicine, expanding it beyond clinical decision-making to encompass broader forms of research and real-world insights in public decision-making *(1,2)*.

EIP relies on integrating diverse forms of evidence drawn from across the evidence ecosystem – such as data analytics, policy evaluation, behavioural and implementation research, qualitative insights, evidence synthesis, cost-effectiveness studies and guidelines *(7–9)*. In health, this includes findings from clinical trials, epidemiological research and health technology assessments *(10)*. This commitment to robust and varied evidence strengthens the transparency, accountability and impact of policy-making *(11)*.

A core tenet of EIP is attention to context, considering factors such as feasibility, equity, stakeholder values, practitioner expertise, lived experience and social, political and organizational considerations *(11–14)*. Scientific rigor, when combined with local insight, ensures that policies are both technically sound and practically relevant, supporting effective implementation even in diverse environments *(10,15–17)*.

The core steps of EIP comprise defining challenges, critically appraising and synthesizing evidence, translating insights into policy, and ongoing monitoring and refinement (Fig. 1). With the rise of digital data and increased analytical capacity, EIP processes are shifting increasingly towards "living evidence" approaches that continuously update syntheses as new insights emerge. This dynamic process positions evidence as an enduring resource for iterative decision-making, rather than as a one-off assessment *(18–20)*.

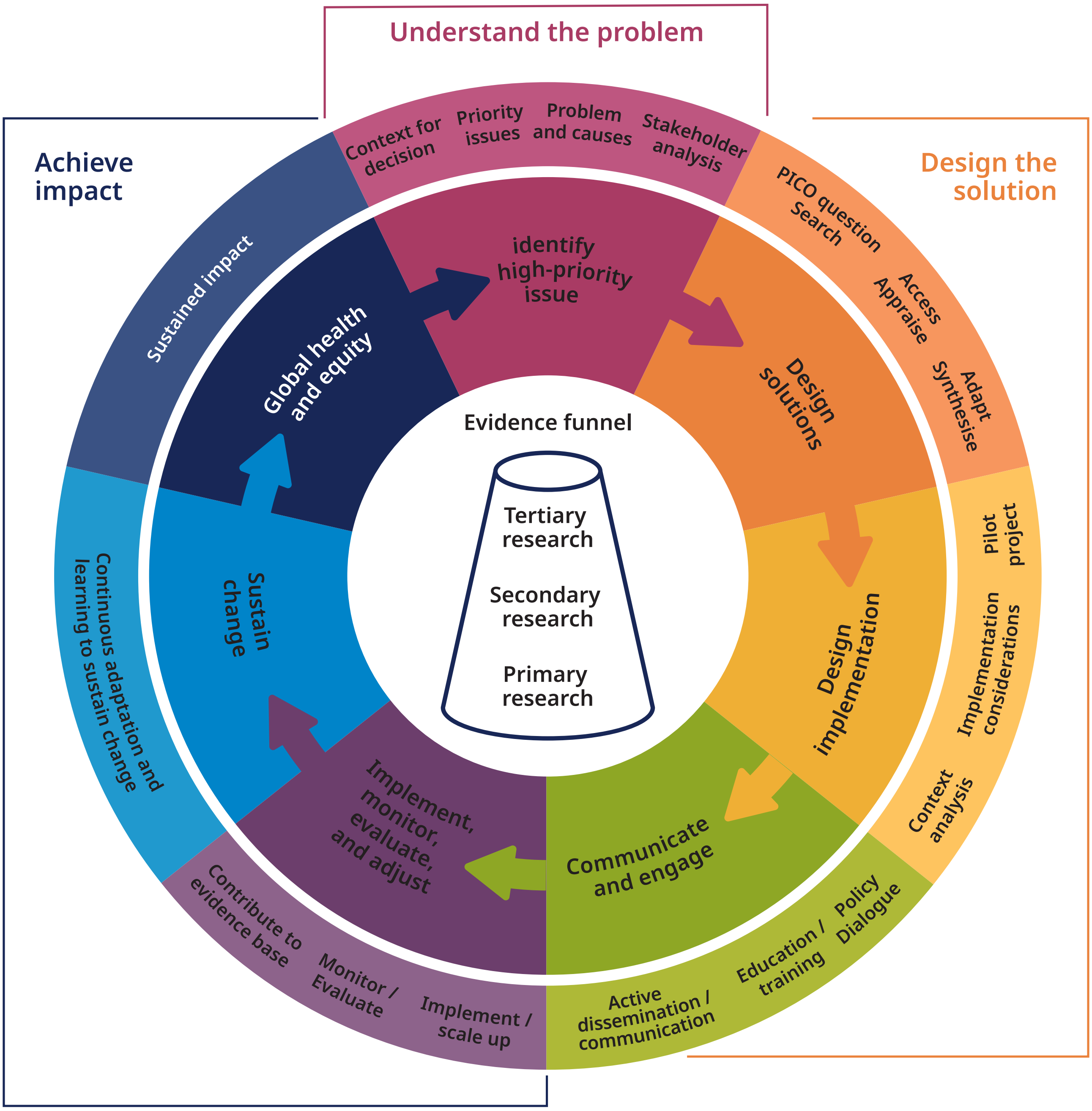

Fig. 1. The evidence-informed decision-making stages (Ref. *(5)*, p.23).

4. Evidence-informed policy-making and artificial intelligence for health: framing the intersection

AI technologies offer powerful tools that augment EIP across its life cycle (Fig. 1), enabling more comprehensive data integration, research synthesis, scenario modeling and adaptive feedback.

While AI has shown promise in some areas of EIP, such as data analysis and modelling, its broader usefulness in EIP remains uncertain – particularly in generating other forms of evidence that are essential to policy-making *(21–24)*. This underscores the need for cautious, context-aware application as the field continues to evolve.

As AI tools improve, their applications may expand across a broader range of EIP functions. Although this brief presents examples of AI applications aligned to distinct policy phases, several of the tools examined below may have applications across multiple stages.

Understanding the problem

By systematically integrating and analysing heterogeneous data – ranging from electronic health records and epidemiological surveillance to genomic and demographic data sets – and by uncovering statistical patterns, correlations and insights, AI can support a deeper understanding of emerging and persistent public health challenges and can inform how health policy problems are defined, prioritized and framed for action *(21,25,26)*.

For instance, predictive models that combine historical epidemiological data, environmental indicators and mobility patterns have advanced the anticipation of outbreaks, risk stratification and forecasting of health-care resource needs *(27,28)*. These AI-driven systems have played a tangible role in enhancing situational awareness and sharpening the definition and prioritization of public health issues, providing policy-makers with timely information for early response *(29)*. Notably, during the COVID-19 pandemic, AI-enabled surveillance systems helped integrate data streams, such as testing rates and hospitalizations, thereby strengthening real-time monitoring and capacity for rapid evidence synthesis at scale *(30–32)*.

Designing the solution

AI supports policy simulation to stress-test interventions before their implementation, thus facilitating evidence-aligned decision-making under uncertainty *(33)*. This includes, for example, projecting estimated caseloads under varying social distancing, vaccination, and travel restrictions during health emergencies *(34,35)*.

AI has also been used to help navigate complex policy spaces and to aid policy ideation by surfacing options and trade-offs in complex problems, thereby improving early-stage design *(36,37)*. Coupled with expert validation, AI can accelerate evidence synthesis by automating labour-intensive systematic review tasks such as searching, screening, appraising and synthesizing data *(22,23)*.

In operations, AI can enhance resource allocation and process management *(38,39)* – such as forecasting hospital admissions *(40,41)* and optimizing vaccine distribution – thereby improving the efficiency and resilience of health systems *(42–44)*.

Achieving impact

AI is being explored in order to enhance communication between policy-makers and the public by analysing feedback from citizens, experts and other stakeholders. Natural language processing tools can extract insights from unstructured data – such as patient feedback, social media and online forums – to capture public sentiment and inform communication strategies *(19,21,45,46)*. These capabilities may support more adaptive and inclusive policy-making by supplying continuous performance feedback and engaging more effectively with communities, including those that may be hesitant or disproportionately affected *(24)*.

By integrating historical and real-time data, AI can also help identify and mitigate prior policy failures – such as ineffective treatment protocols – by fostering iterative, evidence-informed decision-making processes that are adaptive to evolving contexts *(36,47,48)*.

AI can also enable policy-makers to move through the policy cycle more rapidly, facilitating faster hypothesis testing, scenario modelling and iterative refinement. This acceleration allows for more dynamic, adaptive policy-making that can respond to emerging evidence and changing contexts with greater agility than conventional approaches.

5. Risks and challenges of artificial intelligence in evidence-informed policy-making

While AI offers transformative potential, its real-world impact remains context-dependent, often experimental, and surfaces risks in all phases of the policy cycle, which must be proactively managed to ensure responsible and effective use. Although WHO's guidance provides a foundational ethical and regulatory framework for AI in health *(1,2)*, the unique demands of EIP require tailored approaches that are focused on transparency, equity and governance.

Cross-cutting risks and challenges

Opacity and accountability

Many AI systems function as "black boxes" with opaque decision-making processes, thus complicating explainability, transparency and trust *(49–51)*. This is especially true when models are based on hidden, proprietary methods. Large language models may produce inaccurate, fabricated information ("hallucinations") or unverifiable outputs. The unclear liabilities of developers, policy-makers and implementers compound the challenges to governance by making it difficult to assign liability or address grievances in the event of harm.

Power concentration and equity

A few commercial actors dominate AI development, potentially risking the concentration of influence, reduced adaptability to local contexts and widening global inequities, particularly in low- and middle-income countries.

Regulatory gaps

Rapid AI innovation has outpaced legal frameworks, creating uncertainty over compliance, liability and enforcement, which can lead to fragmented regulatory landscapes *(2)*.

Erosion of human expertise and institutional knowledge

Over-reliance on automated systems risks diminishing policy-makers' capacity for critical analysis, contextual interpretation and independent judgement, leading to weakening institutional autonomy, resilience and the ability to challenge AI-generated outputs.

Bias and discrimination

AI that is trained on biased or incomplete data can perpetuate or amplify systemic inequities. Notable instances exemplify the devastating impact of automated discrimination – such as the Netherlands government's use of an algorithm in child care benefit assessments that led to racial profiling and unjust accusations against thousands of families *(52)*. Proxy variables in data sets – such as using income as a substitute for health outcomes – can oversimplify complex relationships and skew resource allocation.

Epistemic injustice and knowledge exclusion

AI systems risk perpetuating epistemic injustice by privileging quantifiable, data-rich evidence from dominant institutions while marginalizing other valuable knowledge sources such as lived experience, local expertise, Indigenous knowledge systems and community-based insights. AI models predominantly developed in data-rich settings may inadequately capture local contexts and constraints in data-scarce environments, overlooking or misrepresenting the realities of diverse settings. This systematically undervalues the knowledge of marginalized groups and contexts, reinforcing power imbalances in what counts as legitimate evidence in policy-making.

Resource intensity

The high costs of AI infrastructure, data acquisition and maintenance – as well as the skilled personnel required to operate AI systems, along with the environmental footprint of large models – raise concerns about sustainability and long-term affordability *(53)*.

Risks by policy phase

While many risks span the policy cycle, their expression varies by stage and their recurrence across phases can compound their impact. The remainder of this section outlines key risks at each phase, drawing on current and emerging AI applications in EIP.

Understanding the problem

- Data bias and misrepresentation: AI may distort policy priorities by being over-reliant on data that are available and overlooking issues affecting groups that are under-represented in data sets, particularly in data-scarce settings.
- Reinforcement of historical bias: Training AI on outdated data can entrench harmful assumptions and structural inequalities.
- Oversimplification of complex issues: AI models may omit critical context and may frame problems incompletely or misleadingly.

- Mis/disinformation: Generative AI can produce misinformation or fabricated evidence, eroding policy debates and public trust.

Designing the solution

- Overoptimization of measurable objectives: AI prioritization of quantifiable outcomes may overlook qualitative metrics and intangible goals such as social cohesion and community well-being.
- Algorithmic narrowness: AI-generated recommendations may overlook interdependencies between policy areas, thereby undermining cross-sectoral coherence.
- Stakeholder exclusion: AI over-reliance on data may sideline lived experience and limit participatory oversight.
- Ethical blind spots: AI may overlook fairness, equity and cultural context when evaluating policy trade-offs.
- Innovation constraints: AI's bias toward past successes may stifle innovation and adaptability to new challenges.
- Legitimacy risks: Delegating decisions to AI can limit public participation, concentrating power in technocratic processes and weakening trust.

Achieving impact

Policy implementation

- Digital divide: Unequal access to AI infrastructure can worsen disparities in policy delivery, with some groups benefiting unfairly.
- Incentive distortions: AI-driven rewards or penalties may trigger unintended behaviours, including gaming of the system.
- Adaptability challenges: AI-informed policies may underperform in novel or rapidly shifting contexts, particularly when the context differs significantly from the training data.
- Cybersecurity and data integrity: AI systems are vulnerable to attacks and breaches, posing threats to programme delivery and public safety.

Monitoring and evaluation

- Overemphasis on quantitative metrics: AI that prioritizes measurable indicators may overlook qualitative factors such as well-being, professional expertise and lived experience.
- Causality and attribution gaps: AI may struggle to link interventions to outcomes in complex, multi-factor settings, thereby weakening evaluations.

- Feedback loop risks: AI that repeatedly uses biased or flawed data can amplify errors and entrench false assumptions.
- Surveillance and privacy risks: AI-driven monitoring can raise ethical concerns about consent, intrusion and misuse of data.

Policy adjustment and termination

- Resistance to change: Dependence on AI outputs may discourage policy revision, even when new evidence emerges.
- Path dependency: AI that favours incremental changes rooted in past patterns may entrench suboptimal directions.
- Policy drift: Subtle biases or misalignments in AI systems can gradually shift policy implementation away from original goals, often without detection.
- Inflexibility: AI systems trained on static data sets may struggle to adapt, potentially leading to outdated policies or the premature termination of effective ones.

Having examined the opportunities that AI offers for evidence-informed policy-making and the risks it poses across the policy cycle, the following sections of the paper move from analysis to guidance. Section 6 explores how existing governance frameworks from both EIP and AI traditions can be aligned and adapted to address the challenges identified above. Section 7 translates these principles into practical, operational considerations for implementation.

6. Insights into governance frameworks for evidence-informed policy-making and artificial intelligence

The opportunities and risks outlined in the preceding sections underscore the need for vigilant, adaptive governance and ethical rigor in integrating AI into EIP. While EIP governance frameworks emphasize transparency, systematic appraisal of evidence, stakeholder engagement and iterative policy refinement, AI governance focuses on technical oversight, life cycle monitoring, accountability and the protection of fundamental rights. Rather than developing entirely new governance structures, this section identifies where these traditions intersect and how existing frameworks can be adapted to address AI-specific challenges in EIP.

Although traditions may have developed independently, identifying where they intersect and complement each other can help policy-makers to adapt existing tools and norms instead of creating new ones from scratch. At the same time, it is essential to recognize any remaining gaps in order to preserve the trustworthiness and transparency of EIP while addressing the novel risks posed by AI.

The frameworks and standards referenced in this section are drawn from established international guidance – including WHO's guidance on AI for Health *(1,2)*, the AI Principles of the Council of the Organisation for Economic Co-operation and Development *(54)*, the European Union's regulation on harmonized rules on artificial intelligence *(55)*, and foundational EIP tools developed through networks such as the Evidence-informed Policy Network *(56,57)*. These examples are illustrative rather than prescriptive and should be adapted to national contexts and institutional capacities.

- **Transparent and auditable decision-making.** EIP frameworks, such as the European Commission's Better Regulation Guidelines, emphasize impact assessment, evaluation and stakeholder consultation *(58–60)*. These align closely with WHO's call for transparency and explainability in AI systems, as well as with requirements for documented assumptions, traceable inputs and reviewable rationales to support accountability and public trust *(1)*.
- **Open government and participatory engagement.** The Open Government Recommendation and AI Principles of the Organisation for Economic Co-operation and Development both emphasize inclusion and multi-stakeholder involvement *(54,61)*, mirroring EIP's consultative processes. WHO further highlights that participatory governance is essential to ensure that AI supports equitable health outcomes and respects diverse societal values *(1,2)*.

- **Data governance and quality.** FAIR data principles (Findable, Accessible, Interoperable, Reusable) set the standard for richly documented data sets with complete metadata and provenance that enable transparent, replicable and robust evidence use in EIP *(62)*. WHO's data principles complement FAIR by treating data as a public good and prioritizing transparency, privacy and trust *(63)*. Evolving AI documentation standards, such as technical model cards and data set provenance records, help policy-makers to assess bias and contextual appropriateness in AI-generated evidence *(64)*.
- **Rights and accountability.** The European Union's General Data Protection Regulation principles promote lawfulness, fairness, transparency and accuracy in data use, with safeguards on automated decision-making *(65)*. These dovetail with WHO's ethical framework which upholds accountability, human autonomy and rights protection as core elements of legitimate, trustworthy AI-augmented EIP *(1,2,66)*.
- **Evidence standards and reporting.** Established EIP tools – such as the evidence briefs of the Evidence-Informed Policy Network *(56,57)*, the SURE guides *(67)*, and the GRADE Evidence-to-Decision Framework *(68,69)* – promote the structured and transparent translation of evidence. These established EIP standards are complemented by AI reporting guidelines, such as CONSORT-AI and TRIPOD+AI, which support validity, replicability and the global harmonization of AI-derived evidence in policy-making *(70–73)*.
- **Risk-based regulation and continuous oversight.** Risk-based regulation is widely adopted in frameworks such as the European Union's AI Act and the United States National Institute of Standards and Technology AI risk management framework, which promote adaptive, life cycle-wide risk management *(55,74)* that aligns with EIP's iterative learning and assessment cycles. Risk-based principles should be applied contextually, with governance models adapted to local needs, priorities and values. WHO's AI governance guidelines reinforce adaptive life-cycle management, including pre-deployment assessment, post-market surveillance, incident reporting and broad public accountability *(1,2)*.

7. Policy and practical considerations for the future of artificial intelligence in evidence-informed policy-making

Building on the governance frameworks and principles outlined previously, Section 7 translates those insights into practical, operational guidance. Where Section 6 identified *which* existing frameworks and standards can guide AI integration into EIP, this section addresses *how* to implement them in practice, offering concrete considerations for the policy-makers, practitioners and AI developers who navigate this evolving landscape.

Navigating an evolving concept of evidence

- Adopting living evidence workflows: Combine automated retrieval with structured human verification to keep syntheses current while highlighting evidence gaps. Sustain investment in reviewer training and data-quality auditing to safeguard rigor.
- Formulating precise, context-specific questions: AI tools perform best when the policy question is tightly scoped. Use clear population–intervention–comparison–outcome (PICO) or analogous frames to align searches with decision needs *(75)*.
- Blending AI outputs with expert judgement: Maintain multidisciplinary panels to assess methodological soundness, policy relevance and ethical implications.
- Applying AI to a broad range of evidence types where appropriate: Consider how computational methods might be used across diverse evidence domains – qualitative and quantitative studies, behavioural insights, implementation research, programme evaluations and economic analyses – to build a more pluralistic and complete evidence base while recognizing the differing requirements of each domain.

Prioritizing augmentation over automation

This means using AI's computational strengths to support – rather than supplant – human deliberation.

- Approaching AI-generated findings as provisional inputs: Humans remain responsible for framing the questions, judging the quality of evidence, interpreting results in their context and weighing ethical considerations *(76,77)*.

- Mapping tasks to comparative advantage: Tasks requiring normative judgement and stakeholder engagement remain in human hands.
- Embedding routine bias and impact assessments: Systematic audits are used to identify hidden biases in training data or model behaviour and to enable corrective action.
- Assembling multidisciplinary oversight teams: Human expertise from sociology, anthropology, psychology, ethics and other relevant fields is drawn on in order to interpret AI outputs in context *(78)*.

Incorporating a policy/action cycle perspective

Map and tailor AI integration to the phases of the policy/action cycle, instead of retrofitting current applications to existing workflows and potentially overlooking the specific requirements of each stage. For example, use:

- horizon-scanning algorithms for agenda-setting;
- causal-inference models for appraisal; and
- implementation dashboards for delivery.

Before deployment, AI tools should undergo a structured appraisal. This may include using:

- technology readiness-level scoring to gauge technical maturity;
- algorithmic impact assessments to assess societal and ethical implications: and
- pilot projects to provide real-world feedback.

Flexible governance frameworks and adaptive protocols should be used to re-scope or retire tools as priorities change. Systematic risk mapping should be employed to address concerns regarding safety, bias and broader social implications.

Bridging the gap between AI for health policy and AI for health-care delivery

While research on AI in clinical tasks has advanced rapidly, a comparable focus on health policy applications remains limited. This potentially results in missed opportunities for influencing access, affordability and quality of care. Redirecting part of the research agenda towards population-level questions could support more equitable and effective health systems.

Actions to support this shift include:

- encouraging interdisciplinary collaboration to adapt proven clinical AI methods to policy-relevant uses;

- convening cross-sector forums and open knowledge-sharing platforms;
- facilitating capacity-building programmes for policy-makers and public health practitioners; and
- targeting investment towards tools designed for health policy challenges, such as equity-sensitive forecasting models or decision dashboards that integrate cost-effectiveness and ethical criteria.

Ensuring a human-in-the-loop governance

Embed robust human oversight, using:

- data provenance reviews;
- bias testing;
- algorithmic impact assessments;
- human-in-the-loop decision gateways;
- post-deployment audits;
- real-time analytics for timely policy adjustments; and
- regulatory sandboxes for safe testing before implementation.

Human-in-the-loop checkpoints should be built in from the beginning and should be maintained through continuous monitoring and evaluation *(79)*.

Combining AI with collective problem-solving and decision-making

Ensure that policy decisions are informed by diverse perspectives and evidence sources *(80,81)* by:

- ensuring equitable access to AI tools and platforms;
- designing systems transparently to sustain public trust;
- embedding robust privacy safeguards to encourage participation; and
- structuring deliberation processes so that computational insights are interpreted within inclusive, participatory forums.

Conclusion

The integration of AI into evidence-informed policy-making presents both material benefits and significant responsibilities. AI can strengthen every stage of the policy cycle – broadening and accelerating evidence generation, supporting the synthesis of diverse sources, and enabling more timely, adaptive responses to complex health challenges.

Realizing these benefits requires ongoing attention to emerging risks and strong governance grounded in transparency, equity and accountability. This includes establishing clear accountability frameworks, mitigating algorithmic bias, safeguarding privacy and assessing tool performance across different contexts. Sustained collaboration between governments, multilateral institutions, researchers and civil society is essential to share best practices and ensure that benefits are distributed fairly and risks are managed effectively.

The considerations outlined in this paper are intended as a foundation for continued dialogue and adaptation. With deliberate integration, robust safeguards and meaningful stakeholder engagement, AI can help advance evidence-informed policy-making, strengthen health systems and improve health outcomes for all.

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