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Sustainable and Responsible Artificial Intelligence Implementation in Healthcare

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Abstract

Artificial Intelligence (AI) has made significant progress over recent decades. However, its deployment in real-world scenarios has highlighted several risks, ranging from technical deficits to ethical concerns. This has prompted the development of theoretical and normative frameworks for Sustainable and Responsible AI Implementation in various sectors. Such frameworks consider different aspects of the AI lifecycle and deployment, yet their specific application to industrial and service sectors remains scarce. Healthcare is one domain where AI promises significant improvements in outcomes, quality, efficiency, and patient experience.

Nevertheless, best practices for Sustainable and Responsible AI Implementation in healthcare have yet to emerge. The interdisciplinarity and complexity of the domain, coupled with the numerous parallel efforts extending the implementation of established AI and machine learning concepts, call for careful and exhaustive synthesis. The methodology therefore synthesizes existing guidelines on data governance, quality, and privacy; Healthcare AI risk assessment and mitigation; Sustainability and Resource Efficiency in AI; Explainable AI; and AI Audit and Compliance. These aspects are contextualized for AI deployment in Healthcare, and compiled into a set of implementation factors for Sustainable and Responsible Healthcare AI. The implementation of these factors is essential for the deployment of AI solutions that minimize negative impacts on patients, society, and the environment and actively seek to create positive effects.

Keywords: *Sustainable Healthcare AI, Responsible AI Implementation, Healthcare Data Governance, Data Quality Assurance, Patient Privacy Protection, Ethical AI Frameworks, Explainable Clinical AI, AI Risk Assessment, Safety and Hazard Analysis, Regulatory Compliance, AI Auditability, Model Transparency, Human in the Loop Systems, Clinical Workflow Integration, Bias Mitigation Strategies, Resource Efficient AI, Environmental Sustainability, Trustworthy AI Systems, Lifecycle Governance, SocioTechnical Accountability.*

I. INTRODUCTION

Artificial Intelligence (AI) provides healthcare systems with various tools and methods to tackle challenges, enhance service quality, and optimize resource utilization. Aiming for more Sustainable and Responsible AI in Healthcare suggested that these dimensions ought to be prioritized by researchers and innovator-developers producing the solutions of consequence for society. However, the urgency of such care, as well as the prospects and approaches for accomplishing that, remain underexplored. Addressing and responding to these issues revealed that the implementation of (Sustainable and Responsible) AI in Healthcare can be curated along the lines of SRAI for Healthcare.

These lines recognize AI as the product of people, conveying both opportunities and adverse effects that cut across the ethical, legal, and social implications domain. Stakeholders applying such solutions are thereby responsible for recognizing, surveilling, and managing associated risks. Instead of private information, the answers focus on the public interest—specifically, on ideas to support Responsible AI deployment with a special emphasis on risk management. They provide inputs on how to consider the SRAI principles, requirements, and guidelines during deployment in the real world, both when directly developing new models and when sourcing proprietary or open-source solutions for integration into service processes and business models.

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➢ *Overview of Sustainable and Responsible AI in Healthcare*

Sustainable AI offers a holistic framework to minimize the negative environmental, social and economic impacts of the design and deployment of AI systems. Responsible AI follows the principles of fairness, privacy and security, reliability, inclusiveness, transparency, accountability and user-centricity. The convergence of these two vital AI frameworks is necessary, particularly when AI is applied in sensitive and data-rich domains, such as healthcare.

Advances in artificial intelligence (AI) and machine learning (ML) technologies facilitate substantial advances across a range of industries, including healthcare. AI and ML methods simplify operations, boost efficiency, improve decision-making quality, and augment human capabilities. Consequently, deployment is likely to rise at a rapid pace, motivated by improvements in business models, developments in supporting technologies, aspirations to enhance quality, acceptable level of computed costs and levels of human assistance. While AI systems can offer significant advantages, the associated risks must be identified and properly managed.

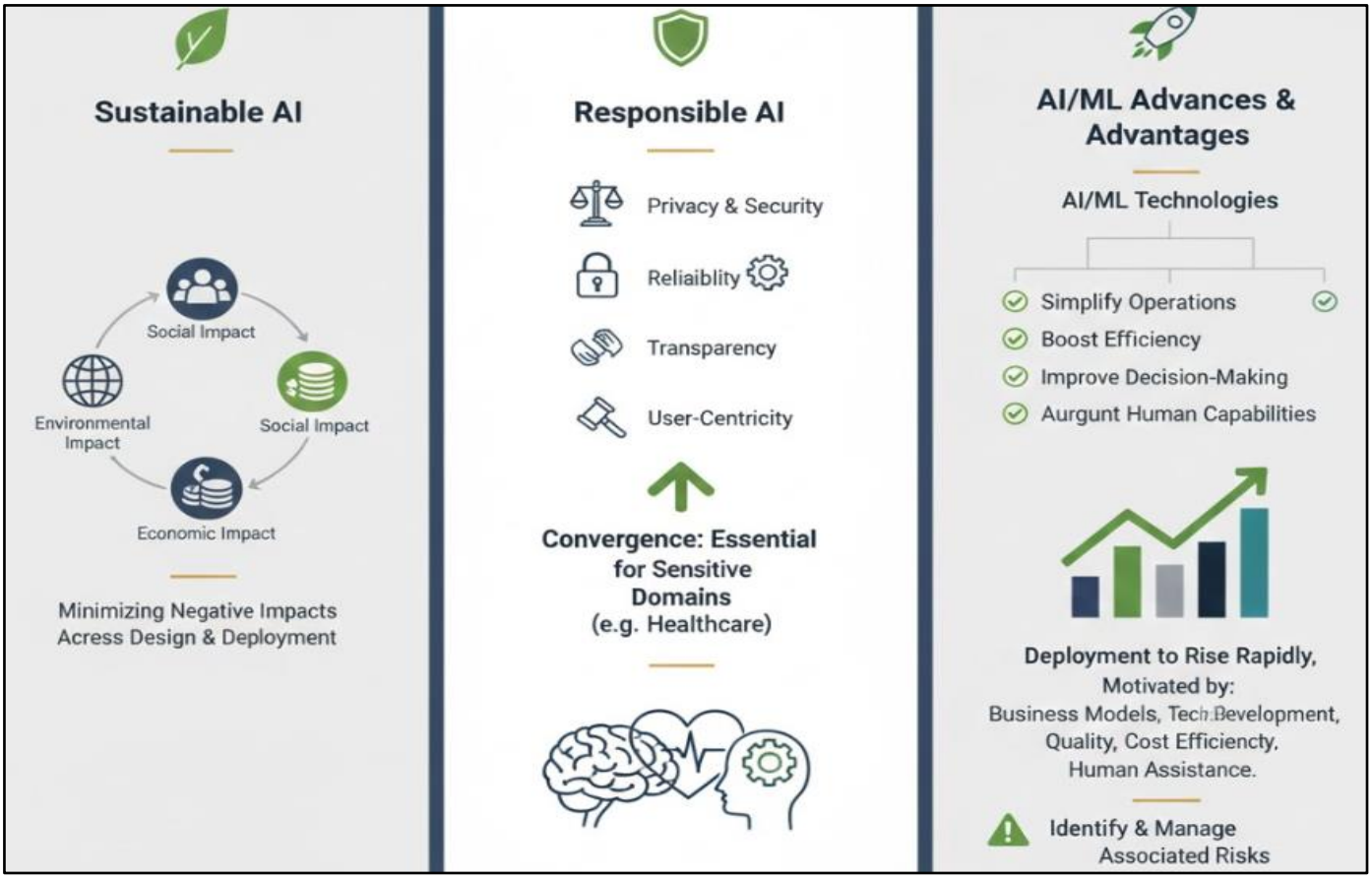

Fig 1 The Synergy of Ethics: Harmonizing Sustainable and Responsible AI in Healthcare

II. CONCEPTUAL FOUNDATIONS OF SUSTAINABLE AND RESPONSIBLE AI

Sustainable AI Implementation for Healthcare encompasses AI solutions capable of supporting clinical practice while complying with legal, regulatory and ethical norms, government policy, and accepted standards of care. The General Ethical Principles for AI offered by the OECD—fairness, transparency, safety, and accountability—serve as a foundation for Responsible AI. In addition, ethical, legal, and social implications must be identified and considered for the proposed system to avoid unintended consequences.

Sustainable AI Implementation in Healthcare requires proposed AI solutions to comply with General Ethical Principles for AI established by authorities such as government regulators, courts, and other responsible oversight entities. Such high-stakes solutions can be classified as "life-critical systems," meaning a malfunction could result in loss of life or significant injury. Users can be experimental subjects, practitioners in the field, or affected persons. AI systems that are self-driving (automated), public-facing (such as facial recognition), or used for high-stakes decisions (law, education, and housing) also require Responsible AI that aligns with the intent of the implementing entity. The proposed AI system must comply with relevant laws, regulations, and ethical concerns. The preferred terminology is "Respectful AI," as that facilitates intention and user engagement and recalls the adage "Respect is earned, not given."

➢ *Defining Sustainability in AI for Healthcare*

Research led by the newly established healthfocused AI industry consortium, Centro Ai within the Italdron Group, takes sustainability and responsibility into consideration. Sustainable AI requires a strategy that accounts for the entire lifecycle—policy, risk management, governance, operationalization of the principles—and includes audit mechanisms. Sustainability

of AI applications in the healthcare sector needs to be considered from different angles and analytic lenses: Sustainable AI must address its ethical, legal, and social implications (ELSI); the risk assessment and risk mitigation process should be formalized; structures for governance and accountability need to be established; regulatory frameworks must be respected; principles and standards for responsible AI must be operationalized and put in place (compliance-by-design); the operationalization must cover all deployment architectures and go-live environments (development, testing, pre-production, and production); deployment and post-production infrastructures must also be sustainable (monitoring, evaluation, and continuous improvement).

The second angle outlined in the document concerns trustworthy and responsible AI. Trustworthy AI must comply with the requirements defined by the European Commission's High Level Expert Group. These principles refer to safety, technical robustness and security, privacy and data governance, transparency, diversity, non-discrimination, fairness, environmental and societal well-being, and accountability. Additional concerns embrace bias in data and algorithms, fairness, explainability and interpretability, risk management and mitigation, compliance with requirements and standards, stakeholder needs, and trade-offs and value choices underpinning AI solutions. Beyond society, the need to balance costs, benefits, and environmental consequences arises, thereby referring to a broader definition of responsibility.

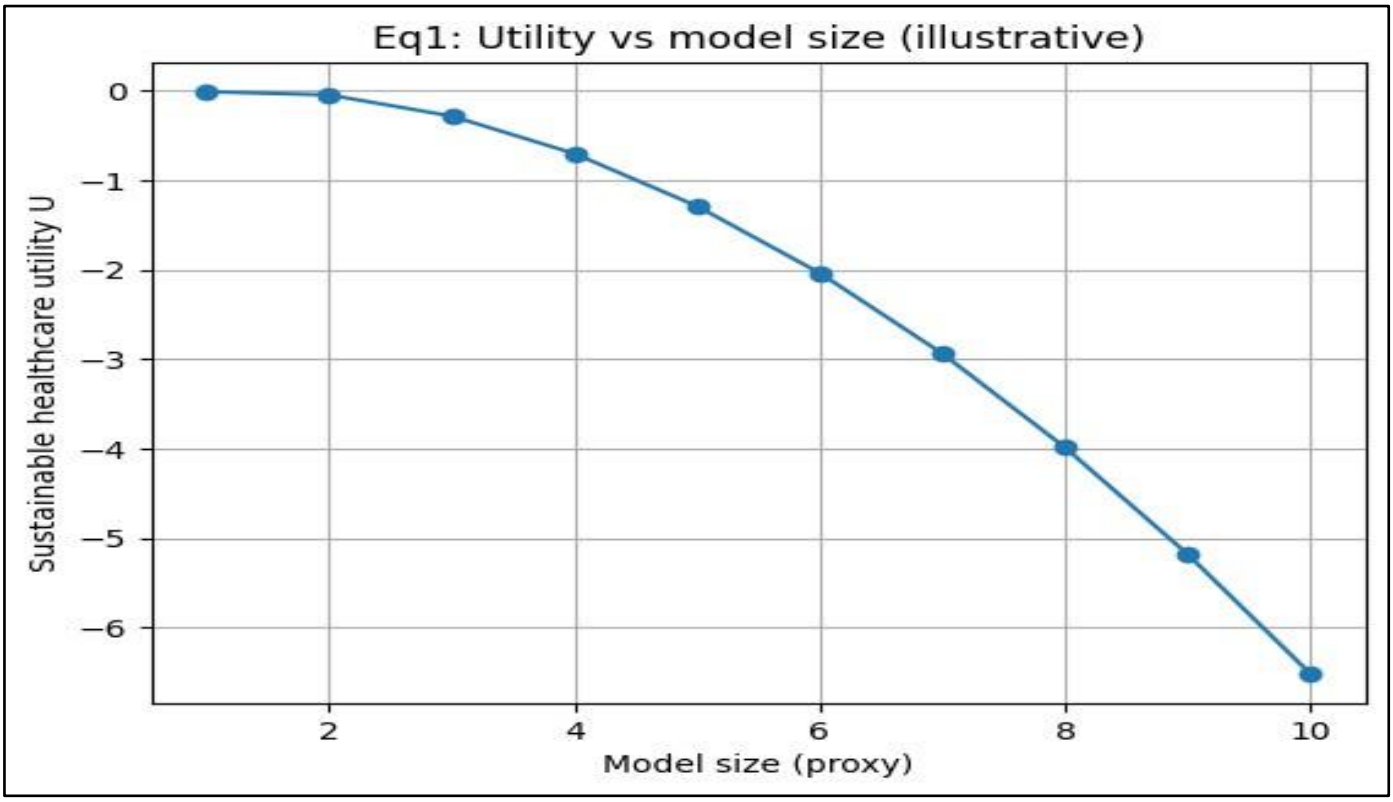

Fig 2 Utility vs Model Size

➢ *Equation 1: Sustainable Healthcare Utility Function*

Step-by-step derivation (from "balance benefits vs. costs/risks")

- Let an AI system configuration be x (model choice, workflow, infra, policies).
- Define measurable components:

✓ Clinical benefit $B(x)$ (e.g., quality-adjusted outcomes, sensitivity, time saved)

✓ Environmental burden $E(x)$ (energy/carbon over lifecycle)

✓ Monetary cost $C(x)$ (deployment + maintenance)

✓ Social/ethical harm $S(x)$ (inequity, safety events, workflow burden)

- Convert this into a single decision score using weights (value choices):

$$U(x) = w_B\, B(x) - w_E\, E(x) - w_C\, C(x) - w_S\, S(x), \quad w_B, w_E, w_C, w_S \geq 0$$

- If your measures are in different units, normalize each term:

$$\tilde{B}(x) = \frac{B(x) - B_{\min}}{B_{\max} - B_{\min}}, \quad \tilde{E}(x) = \frac{E(x) - E_{\min}}{E_{\max} - E_{\min}}, \text{ etc.}$$

And use $U(x) = w_B \tilde{B}(x) - w_E \tilde{E}(x) - w_C \tilde{C}(x) - w_S \tilde{S}(x)$.

Table 1 Model Size vs Clinical Benefit, Energy Cost, Monetary Cost, Social Risk, and Utility

ModelSize	ClinicalBenefit	EnergyCost	MonetaryCost	SocialRisk	Utility
1	0.2953	0.08	0.15	0.2352	-0.0088
2	0.5034	0.32	0.36	0.2252	-0.0447
3	0.6501	0.72	0.63	0.2194	-0.2815
4	0.7534	1.28	0.96	0.2172	-0.7004
5	0.8262	2.00	1.35	0.2181	-1.2882
6	0.8775	2.88	1.80	0.2215	-2.0299
7	0.9137	3.92	2.31	0.2270	-2.9104
8	0.9392	5.12	2.88	0.2345	-3.9148
9	0.9573	6.48	3.51	0.2438	-5.0296
10	0.9700	8.00	4.20	0.2547	-6.2424

➢ *Principles of Responsible AI*

Principles of Responsible AI informs practitioners implementing AI in healthcare of the prevalent ethical requirements and risk mitigation and assurance principles to follow. The traditional approach of merely satisfying legal requirements is no longer sufficient; AI should also be assessed and managed for the ethical issues it can create, especially for the specific healthcare population or problem being addressed. Graduate or doctoral-quality education should prepare practitioners to identify ethical issues a proposed or deployed system may create and to propose risk mitigation or assurance mechanisms that prepare for, eliminate, or reduce those issues. The principles described are often used in such education.

- *The Following are Ten Ethical Principles or Requirements Commonly Referenced in the Literature on Responsible AI:*

✓ ***Accountability**:*

Every AI system should have a principal or set of individuals accountable for the ethical operation of the system. Such accountability should be formally assigned, including appropriate organizational structure and support.

✓ ***Confidentiality**:*

The confidentiality of data used to develop, evaluate, or deploy AI systems should be protected for the individuals or organizations to which it pertains.

✓ ***Fairness**:*

Bias in the predictions made by AI systems on protected groups or classes (as defined by the healthcare application or domain under consideration) should be avoided, mitigated, or otherwise accounted for to the extent possible. The principles behind fairness are treated in more detail. It should also be noted, however, that absolute fairness (as defined by any metric) can be impossible to achieve.

✓ ***Human Control**:*

A principal or team of individuals should have the authority and means to intervene in the operation of an AI system and alter its operation, including the ability to shut it down, if that proves necessary.

➢ *Ethical, Legal, and Social Implications*

The ethical, legal, and social implications (ELSI) of AI are complex and manifold. They must be addressed throughout the design and deployment lifecycle of the technology. Relying solely on a set of design principles is insufficient, especially when a service or product affects human rights. In such cases, explicit assessments and critiques from a diverse and well-informed group of ELSI specialists—using the appropriate methods and procedures for eliciting criticism and exploring alternatives—are necessary to ensure that negative impact will be minimized or negated.

Healthcare applications of AI bring a high risk of magnifying and unfairly reproducing structural systemic prejudices. These risks can lead to ethical failures and are being questioned by rights groups. Similarly, technologies for nudging and deception—such as emotion recognition, targeted communications, and information pollution—can manipulate and exploit the vulnerabilities of patient populations. The policing industries also employ methods that extract or infer sensitive information from behavior traces. Extreme-fidelity surveillance can also give rise to security problems and precipitate anxiety in both patients and hospital visitors. ELSI assessment, conception, and criticism therefore demand robust and extensive engagement with diverse medicinal domains and AI deployment deployments therein.

III. HEALTHCARE CONTEXT AND AI DEPLOYMENT

Healthcare, like many other sectors, currently faces significant AI hype. Addressing the "what", "where", "when", and "how" associated with AI deployment is pivotal to ensuring that value is created and that the substantive challenges–data governance and privacy, data quality and fairness, and interoperability and standards–that must be resolved most quickly can be prioritized and appropriately resourced. AI has the potential to improve the healthcare system by providing new methods to detect, diagnose, or treat disease but the needs for sovereignty of data, the need for explainability, and the difficulty of proving fairness, even with very high-quality AI, must all be recognized. These attributes are part of a broader context in which the risks of AI are understood and mitigated at every step of the development process, either by avoiding risky applications or by adding a risk mitigation layer to the model applications.

The implementation of AI must be orchestrated in such a way as to embed and reinforce six contextual

pillars, which must operate collectively to sustain responsible AI in practice. These pillars are (1) governance and risk management, (2) monitoring and measurement, (3) deployment infrastructure, (4) workforce change management, (5) immediate outcomes from deployment, and (6) continuous improvement. Continuing investment is a characteristic of many aspects of AI. The nature of deployment infrastructure gives the productivity gains of AI in the provision of AI-enabled services. The value of AI is enhanced when outcomes can be measured and are fed back into the AI's decision-making processes. These two pillars support the pillars of risk assessment and mitigation and the foundations of stakeholder engagement. Hydraulic folding and unfolding of the pillars and foundations keeps the workflows stable even in the face of failures.

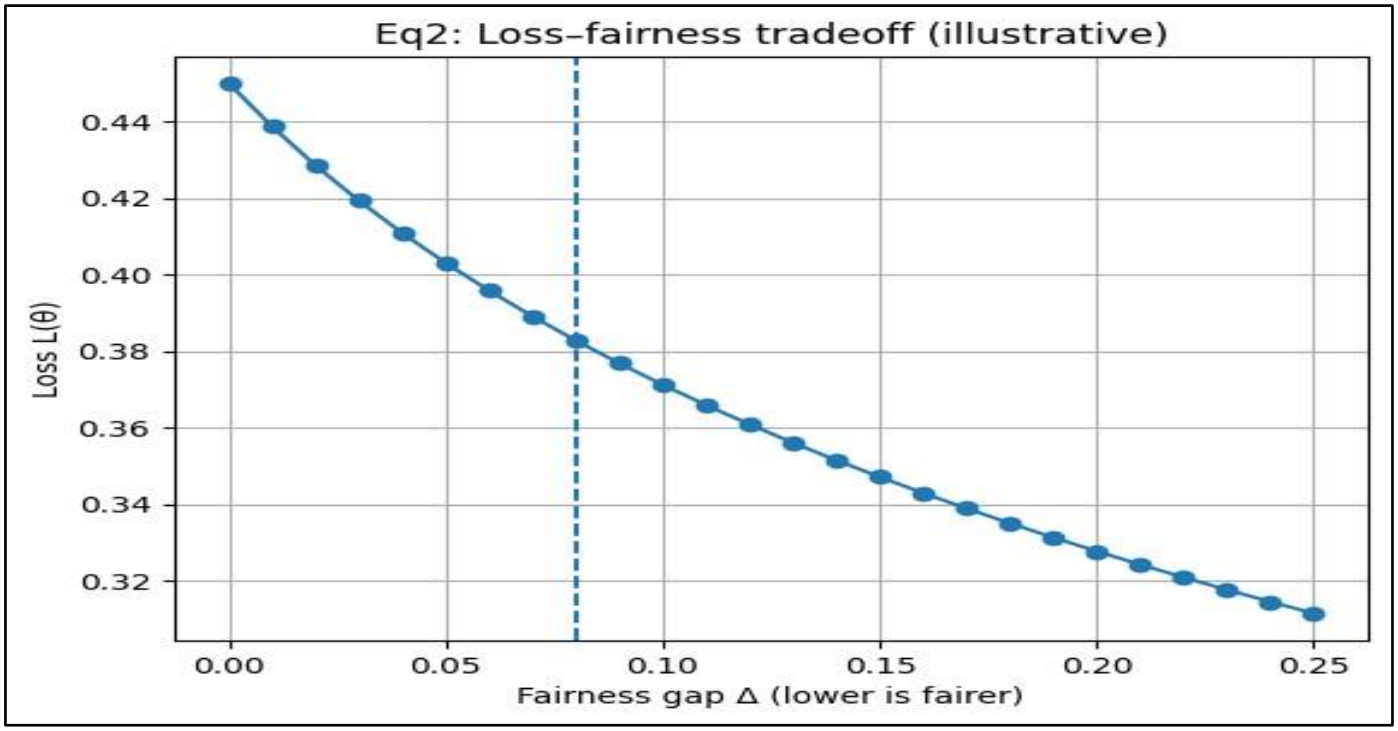

Fig 3 Loss-Fairness Tradeoff (Illustrative)

- *Equation 2: Fairness-Constrained Optimization Objective*

- *Step-by-Step Derivation*

✓ Let model parameters be θ.
✓ Define the task loss on clinical data:

$$L(\theta) = \mathbb{E}_{(x,y)}[\ell(f_\theta(x), y)]$$

✓ Pick a fairness metric $\Delta(\theta)$ (examples: demographic parity gap, equalized odds gap).
✓ Require fairness gap not exceed threshold ε:

$$\min_\theta L(\theta) \quad \text{s.t.} \quad \Delta(\theta) \le \varepsilon$$

✓ Convert constraint to an unconstrained form (Lagrangian):

$$\mathcal{L}(\theta, \lambda) = L(\theta) + \lambda(\Delta(\theta) - \varepsilon), \quad \lambda \ge 0$$

✓ Optimization conditions (KKT):

- Stationarity: $\nabla_\theta L(\theta) + \lambda \nabla_\theta \Delta(\theta) = 0$
- Primal feasibility: $\Delta(\theta) \le \varepsilon$
- Dual feasibility: $\lambda \ge 0$
- Complementary slackness: $\lambda(\Delta(\theta) - \varepsilon) = 0$

➢ *Data Governance and Privacy*

AI adoption in healthcare raises sensitive considerations concerning the risks of data sharing. Information about patients that is used for training must be secured and protected so that it cannot be misused. Breaching such privacy not only violates the moral contract but can also result in heavy financial penalties for vendors in cases of mishaps. Data governance and privacy require embedding relevant practices in the healthcare ecosystem and securing them through third-party audits per regulatory requirements. Indeed, the absence of rigorous compliance checks has led to numerous incidents involving severe penalties imposed on companies.

Privacy risks associated with the data are not only related to how and where these data are stored and processed, but also to who is sharing access with whom. There is an inherent risk of compromise when a large number of parties are involved in policy decisions that have an effect on privacy management. Hence, attention needs to be given to limiting the number of such parties. A central institution must offer APIs to all parties in either a centralized or decentralized manner while being equipped with strong authentication and access-control processes and following auditing and reporting compliance checks. This institution must control access to data, manage the necessary data-sharing agreements, and carry out periodic audits to obtain compliance verification certificates.

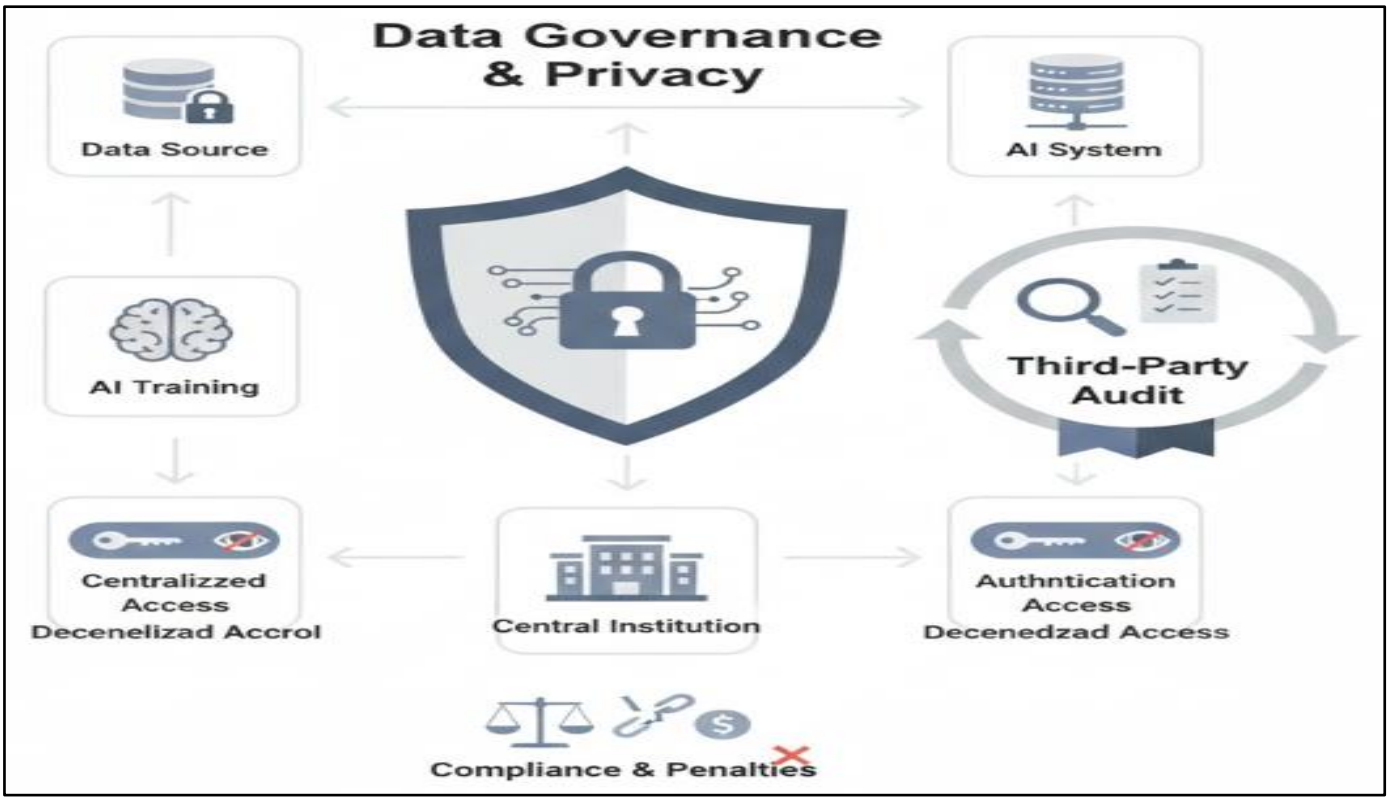

Fig 4 Structural Integrity in Healthcare AI: A Governance Framework for Data Sovereignty, Regulatory Compliance, and Risk-Mitigated Access Control

➢ *Data Quality, Bias, and Fairness*

AI systems depend on extensive data for training and testing and on associated features for operational objectives, performance evaluation, and ground-truth data. It is crucial to ensure that the used datasets include the representation required for AI systems that make important healthcare decisions, as well as for any performance evaluation. It must be noted that the objectives of AI applications in healthcare are mostly different from predictive tasks found in other domains. A trained AI system will be engaged with images, text, or signals that are substantially dissimilar from its training and that require identifying abnormalities and unknown classes to answer a clinical question. Therefore, the decision or failure of the system does not pertain to prediction or recognition, but to making optimally informed decisions that impact the lives of patients, and consequently the testing and evaluation datasets need to represent the testing images better than the training images. AI systems in general must be qualified as risk-sensitive applications by healthcare institutions deploying such AI systems.

Fairness and bias in AI-based healthcare systems are also vital concerns. Heuristic solutions include the cautious selection of the training dataset, performance evaluation with balanced datasets, stakeholder engagement, introducing diverse user scenarios, interpretability by clinical personnel for multiple demographic subgroups, training bias-detection tools, etc. Comprehensive and systematic remedies for bias in AI for healthcare must include a dedicated strategy focused on addressing bias at all stages of development, testing, deployment, and clinical supervision, along with engaging the relevant stakeholders. Possible action areas related to bias in AI for healthcare are guidance early in the project, developing a clinical use case of the system, looking to the operational scenario, addressing the AI development lifecycle, including evaluation and deployment, and exhausting all areas actively related to AI for healthcare.

➢ *Interoperability and Standards*

Sustainable and responsible AI in healthcare should foster interoperability and consistency with existing systems, standards, and regulations. Interoperability facilitates secure sharing, linking, and collaborative use of data across organizations. By increasing the range of potential data sources, interoperability spans many modes of delivery, introduces diverse stakeholders, and opens new contexts of care. Technical, semantic, and prospective interoperability reduce the risk of bias and increase system robustness. Interoperability should be supported by standards and persist throughout entire AI lifecycles and ecosystem operations.

Achieving and maintaining the requisite standard of interoperability increases a sustainable–responsible AI system's security cost, risk, and time requirements. Given the emphasis on the social dimension of sustainability, national and international cybersecurity standards for best practices in protecting organizational networks, data, and services must be established and enforced. Standardizing labeled data formats enables easy monitoring for data drift. Assessing data drift offers insight about re-training frequency. To facilitate compliance with laws and regulation that govern the protection of data, design, implementation, and delivery processes should incorporate appropriate technical and organizational measures; oversight must be established to direct these measures.

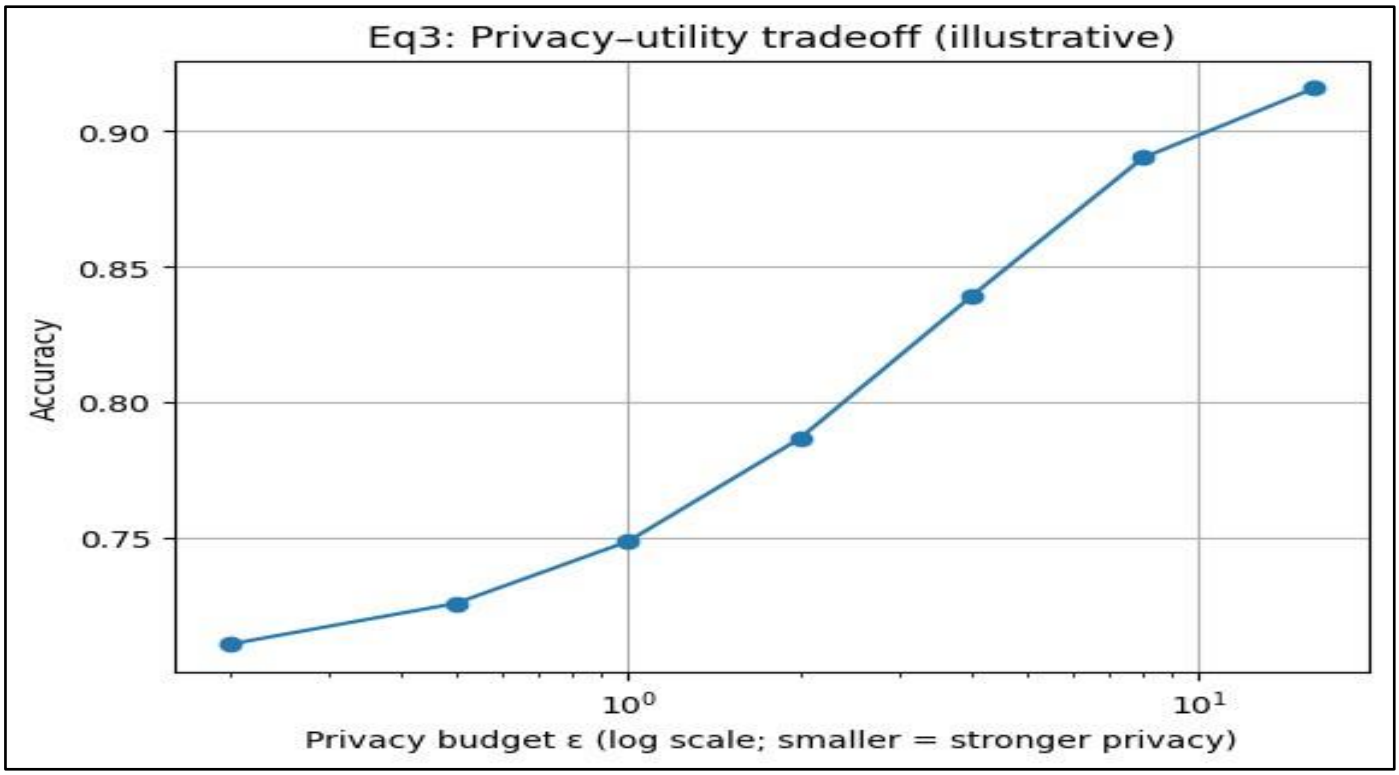

Fig 5 Privacy -Utility Tradeoff

- *Equation 3: Privacy-Preserving Learning Constraint*

Step-by-step derivation using Differential Privacy (DP)

✓ Let training algorithm be A that maps dataset D to a model.
✓ Neighboring datasets D and D' differ by one patient record.
✓ (ε, δ)-DP definition:

$$\Pr[A(D) \in S] \leq e^{\varepsilon} \Pr[A(D') \in S] + \delta \quad \forall S$$

✓ Turn this into a *constraint* during training:

$$\min_{\theta} L(\theta) \quad \text{s.t.} \quad \text{Training procedure is } (\varepsilon, \delta)\text{-DP}$$

✓ Practical enforcement (DP-SGD sketch):

- Clip per-example gradients: $g_i \leftarrow g_i / \max(1, \| g_i \|_2 / C)$
- Add Gaussian noise: $\bar{g} = \frac{1}{n} \sum_i g_i + \mathcal{N}(0, \sigma^2 C^2 I)$
- Update: $\theta \leftarrow \theta - \eta \bar{g}$

✓ As noise σ increases, ε decreases (stronger privacy), typically reducing accuracy.

IV. METHODOLOGIES FOR SUSTAINABLE AI

Sustainable AI implementation can be approached through several methodologies for minimizing its impact while ensuring desirable outcomes. The environmental costs associated with training AI models can be evaluated using lifecycle assessment (LCA) to help prioritize model capability and resource efficiency. This is particularly important for the training of large language models (LLMs) and generative adversarial networks (GANs), which require massive amounts of energy and carbon footprint. Regarding prediction, adequate resources for aiding human decision-making in high-stakes areas such as healthcare can be deployed with a focus on all dimensions of AI strategy focused on risk management and equity.

Impact assessment should also extend beyond environmental consequences. Explainability, auditability, transparency, and accountability are vital for facilitating effective human interaction with AI systems. An inclusive and human-centric approach to design, based on engagement with diverse stakeholders, helps to identify and address potential negative consequences of AI deployment throughout its entire lifecycle. Furthermore, monitoring against the potential detrimental impact of predictions on different population groups fosters a focus on all dimensions of AI strategy aligned with risk management and equity, extending to change-management mechanisms that prepare the organization and workforce for new modes of operation.

➢ *Lifecycle Assessment and Impact*

Strategic intervention points for risk mitigation are often identified through Risk Assessment. However, Risk Assessment alone cannot guarantee Risk Elimination. Additional techniques—such as development, integration, and evaluation—also play critical roles in reducing Risk levels. Therefore, the concept of Risk Management embraces a broader range of life-cycle activities than the term "Risk Assessment" might imply.

Sustainable and Responsible AI places particular emphasis on these activities and recommends that the

following methodologies are employed to minimize the Environmental, Social, and Governance footprint of AI systems. Lifecycle Assessment (LCA) is used to evaluate the cradle-to-grave Environmental impact of a product or service. Apart from the Environmental dimension, the Sustainable AI for Healthcare literature has also cited other AI Lifecycle Assessment initiatives that aim to quantify the Social and/or Governance aspects of AI.

➢ *Resource-Efficient Model Development*

Sustainable AI also involves the application of resource-efficiency methods throughout the model training and development process, such as pruning or quantization, which optimize memory requirements and inference efficiency. These methods complement explainable AI methods (4.3) that assist in benchmarking the model complexity. Given the massive data center requirements for training large-scale models—such as chat platforms with multi-trillion parameters—and the uptake of heavier models in general, further resource-efficient development is essential for reducing energy and other resource consumption, contributing to sustainability. Resource-efficient or resource-aware AI comprises a range of allied development methodologies aimed at reducing the resource burden of training and deploying AI solutions, applied on the one hand to the training and development workload and on the other to the burdens associated with inference and operation.

For language models with billions and trillions of parameters, energy and carbon emissions in the training phase alone are staggering. For example, the carbon emission estimates for training a single model range from 77 to 215 tons of CO2eq and up to 950 tons for ChatGPT. Pragmatically, deploying smaller and lighter models requires tuning smaller pre-trained models for target domains and applications. Aiming at the same goals and with similar considerations, few-shot or zero-shot learning provides a practical approach to the problem of large-scale data and training in an area where the demand for language processing exceeds industry-researched end-to-end implementations. While the method expounded here is germane to natural language, other resource-efficient alternatives span efforts to promote model compression through quantization and pruning of dense transformer architectures and attention models and beyond natural language to visual recognition, generation, and other domains.

- Equation 4: Trust-Aware Clinical Risk Function
  Step-by-step derivation

✓ Let clinical state be s, model output $a = f_\theta(x)$, and true action a^*.

✓ Define harm (severity-weighted loss):

$$h(a, a^*, s) \geq 0$$

✓ Expected clinical risk:

$$R(\theta) = \mathbb{E}[h(f_\theta(x), a^*, s)]$$

✓ Add "trust/calibration" because over-trust increases harm when wrong:

- Let $c(x)$ be model confidence; let $p(y \mid x)$ be true correctness probability.
- Calibration error $k(x) = |c(x) - p(y \mid x)|$

✓ Trust-aware risk multiplier:

$$R_T(\theta) = \mathbb{E}\big[h(\cdot)\,(1 + \alpha\, k(x))\big], \quad \alpha \geq 0$$

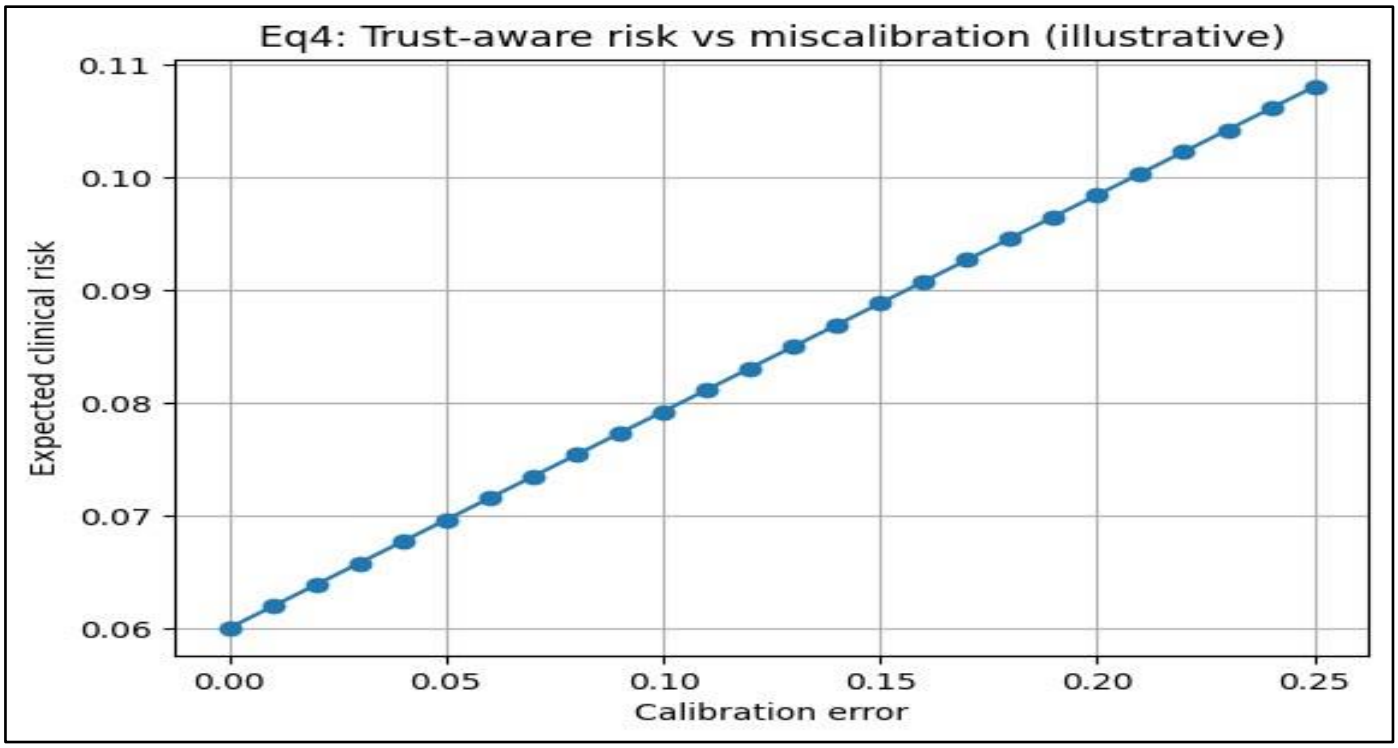

Fig 6 Trust-Aware Risk vs Miscalibration

Table 2 Calibration Error vs Expected Risk (Trust-Aware Risk Table)

CalibrationError	ExpectedRisk
0.00	0.0600
0.05	0.0696
0.10	0.0792
0.15	0.0888
0.20	0.0984
0.25	0.1080

- *Explainability, Auditability, and Transparency*

While recent breakthroughs in AI performance hold great promise, the underlying mechanisms often remain unintelligible even to the developers themselves. For many AI applications—especially in sensitive domains like healthcare, finance, and criminal justice—explainability is crucial to ensuring trust, facilitating better decision-making, and allowing for accountability. Auditable systems are equally important to ascertain compliance with legal and regulatory frameworks. Practitioners propose various means of improving explainability and auditability, including integrating popularly used interpretive techniques into model-development pipelines to explain AI decisions.

Some stakeholders support monitoring of AI systems by dedicated "AI inquiry teams" tasked with safeguarding sAI and rAI principles. These teams could engage an extensive network of AI specialists and social scientists across institutions to evaluate the implications of deployed AI systems and support the creation of specific safeguards. A separate recommendation for successive evaluations of AI systems complements the inquiry team proposal. Organizations could conduct regular retrospective assessments of production AI systems at pre-defined intervals, or more frequently if warranted, to ascertain effectiveness, safety, and compliance.

Transparency is especially critical to robust and reliable AI. AI systems should be transparent across the full value chain, explaining their purposes and functionalities, their data pipelines, any inherent limitations, and how the deployment reflects sAI and rAI principles. Such transparency is essential for users—and especially the end beneficiaries—fully to understand and trust AI systems.

- *Human-Centric Design and Stakeholder Engagement*

Human-centred AI design enhances technology accessibility, usability, and acceptance, therefore contributing to widespread adoption, performance, and safety. Stakeholder engagement is essential to identify interested parties, their areas of interest, and how they might benefit or bear the costs of the technology. Involving stakeholders in a meaningful way over the entire lifecycle is indispensable for reducing risks and improving acceptance.

Stakeholders should participate in the project from its conception. For example, defining the use case, collecting the requirements, and determining the feasibility of the selected ideas should involve healthcare professionals, patients, and IT departments at a minimum. In general, the organization expecting to deploy the AI application should actively participate in all phases of the project, not limiting its involvement to data labeling, recruiting test participants, and estimating the implementation costs. Far too often, these extremely important phases are considered a mere formality and remain factual formalities. Involving stakeholders in decisions concerning performance measures or potentially sensitive issues, such as user trust and acceptance, also is essential.

Participating in requirements engineering presents yet another advantage: stakeholders assist in establishing acceptance criteria. Ideally, these criteria should be expressed as monetary values (return-on-investment estimates), as humanitarian criteria (e.g., saving patient lives in real-world patient treatment with reasonable costs, serving underserved health areas), or as a combination of these criteria. Stakeholders also can play a crucial role in evaluating the AI application—during the testing phase. Ideally, testing should be executed before a wider rollout.

V. RISK MANAGEMENT AND ACCOUNTABILITY FRAMEWORKS

The Sustainable AI Framework outlines key risk assessment and mitigation stages alongside the governance structures, regulatory compliance requirements, and compliance-by-design mechanisms needed to support responsible AI deployment. Risk assessment encapsulates the product risk profile, focussing on potential harm caused rather than risk likelihood; certification or standardization requirements governing these risks; risk-mitigation measures established during design and development; and any particular elements of the risk assessment framework that support continuous audit of behaviours during operational deployment.

Governance structures define the humans ultimately accountable for control and oversight, as well as enabling third-party audit processes. Regulatory compliance requirements specify applicable jurisdictional, temporal, and product-context conditions relevant to adherence to AI-specific regulations and AI-relevant aspects embedded in wider regulations. The compliance-by-design mechanism identifies and implements such processes unsystematically during model development, providing confidence that usage of the AI does not breach even certification and approval requirements.

Accountability is simultaneously encompassed in risk assessment and articulated as a distinct topic in an accompanying checklist. The distinction highlights that assurance of product safety before and during usage

requires more than governance structure definition. Products may require accompaniment by third-party assessors in addition to supporting relevant procedures, including human examination of hazard responses at limited operating scope and audit of behaviours in actual deployment.

➢ *Risk Assessment and Mitigation*

Comprehensive risk assessment and mitigation are essential in AI-enabled healthcare. Adversarial and purposeful manipulation, as well as unintentional interaction failures, require careful examination and validation before deployment. Toolkits that aid in coverage testing, risk mitigation, and ethics checklists are beneficial throughout the development and deployment process. Existing methodologies that typically focus on safety assessment can be extended to include adversarial robustness, usability under failures, and ethical/coverage testing. Conducting a risk assessment before deployment allows for adequate implementation and monitoring triangulation steps in risk oversight**.** Adverse-matter guidance describes a continuous monitoring process that follows the monitoring of changes in underlying data and model drift. An AI-powered medical decision support system that offers a contrast to traditional radiological evaluations poses an additional concern. Malicious modifications and unintentional misuses require comprehensive coverage tests, including destructive and restorative abuse, actor substitution, installation failure, and context change. Traveling by air represents an interaction that may occur in a different context, and such coverage-testing methods can offer invaluable assistance. A change to AI-enabled systems includes the discovery that fusion approaches may not provide robustness against redundancy-failure abuse, and this risk is covered methodically.

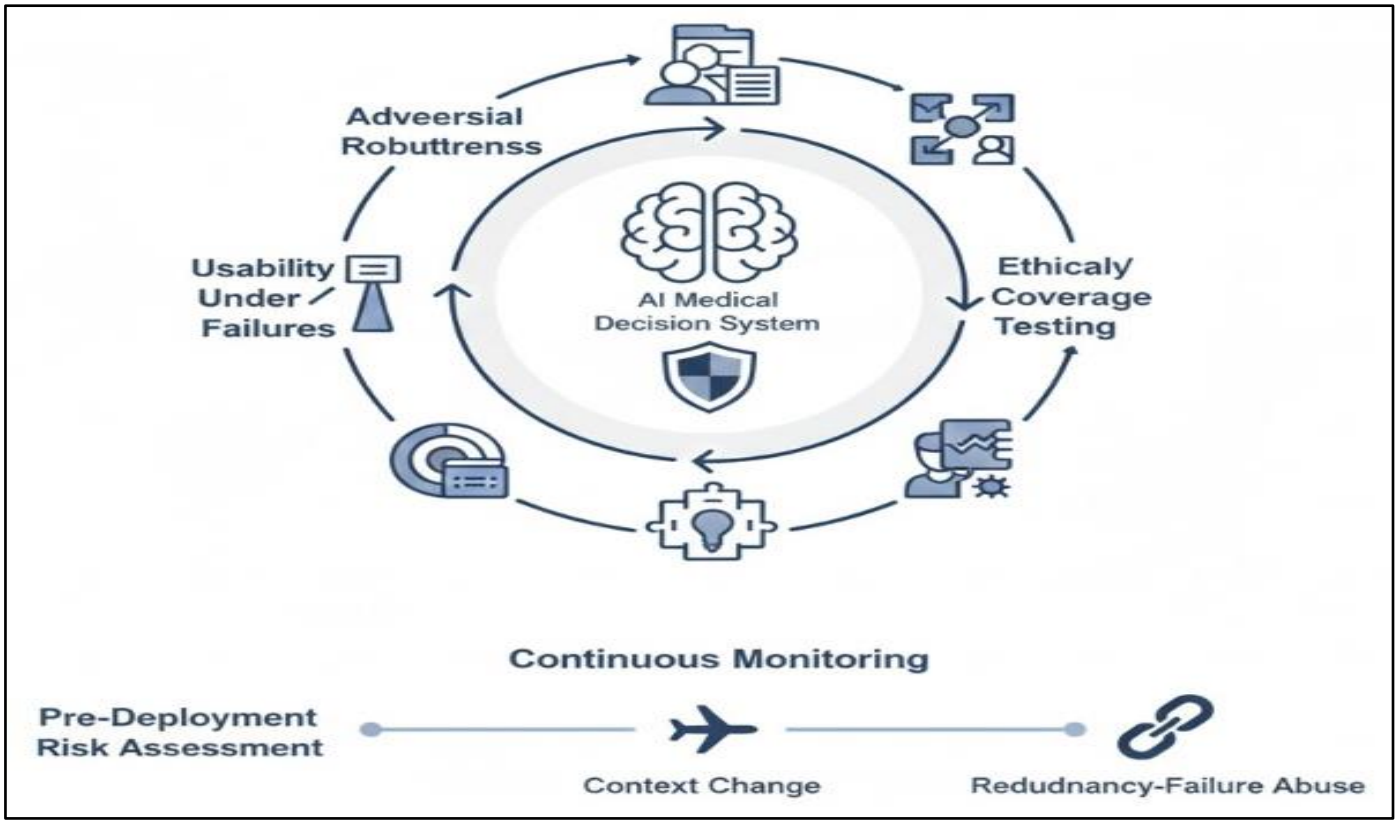

Fig 7 Beyond Safety: A Triangulated Risk-Oversight Framework for Adversarial Robustness and Model Drift in Clinical AI Systems

➢ *Governance Structures and Accountability*

Effective governance structures define the people and processes responsible for managing AI systems throughout their lifecycle. Regular risk assessments mitigate undesirable outcomes and performance failures. Governance and risk management tasks are best carried out by interdisciplinary, multi-stakeholder teams. Adequate resources, budgets, and change management are essential to ensuring AI systems function as intended.

The structures and overseers of AI systems should be defined and established before taking these systems into active use. Even before deployment, examining the expected impact of an AI technology on its environment allows for the preparation of adequate governance, risk mitigation methods, and appropriate budget allocation. A primary body should be accountable for the AI, with the power to call for tools such as simulations, explainability, monitoring, and periodic auditing. If the AI is affecting multiple stakeholders, a multidisciplinary, multistakeholder group should perform these tasks. Otherwise, a single product-team member—ideally with particular concern for Human-Centric Design processes—should manage these oversight responsibilities.

Adequate resources and budget are necessary for regularly scheduled risk assessments. Such assessments should be ongoing, as part of a Change Management strategy, rather than limited to a compliance check before deployment. Sufficient resources for mitigation actions,

sufficient budget to accommodate AI technology updates, and an appropriate schedule for taking AI technologies out of service and redoing their assessments and mitigations are all required.

➢ *Regulatory Compliance and Compliance-by-Design*

Regulatory compliance is critical, given AI healthcare applications' potential to cause both physical harm and exacerbation of health inequalities. Identified risks must be carefully defined and measured, and monitoring strategies must be proportionate. Mitigating regulatory risks and ensuring ongoing compliance should be integrated into all internal or external projects and services. Regulatory finders—tools that link functionalities of an AI solution with relevant regulatory texts and guidelines—allow for risk assessment and mitigation and ongoing precautionary measures and self-checks throughout the AI project life cycle. Currently, many AI projects achieve compliance by passing requirements checks at the deployment stage, often without devoting adequate resources. To improve the compliance burden, compliance-by-design approaches offer a viable option.

Compliance-by-design responds to two fundamental issues: (1) expanding regulatory criteria to encompass the complete life cycle of an AI project and (2) integrating those criteria into the various project life cycle stages, from inception to daily operation. Addressing the first issue requires regulatory orders to connect the AI system, project development and use case with any correlated regulatory text, in a lucid and accessible way, during each stage of the system's life cycle. For the second, compliance-by-design advocates for a two-level control gate. At level 1, a regulatory finder verifies that AI data collection and label creation are suitable for the intended AI deployment. At level 2, it confirms that the AI performance for the intended health use case is satisfactory.

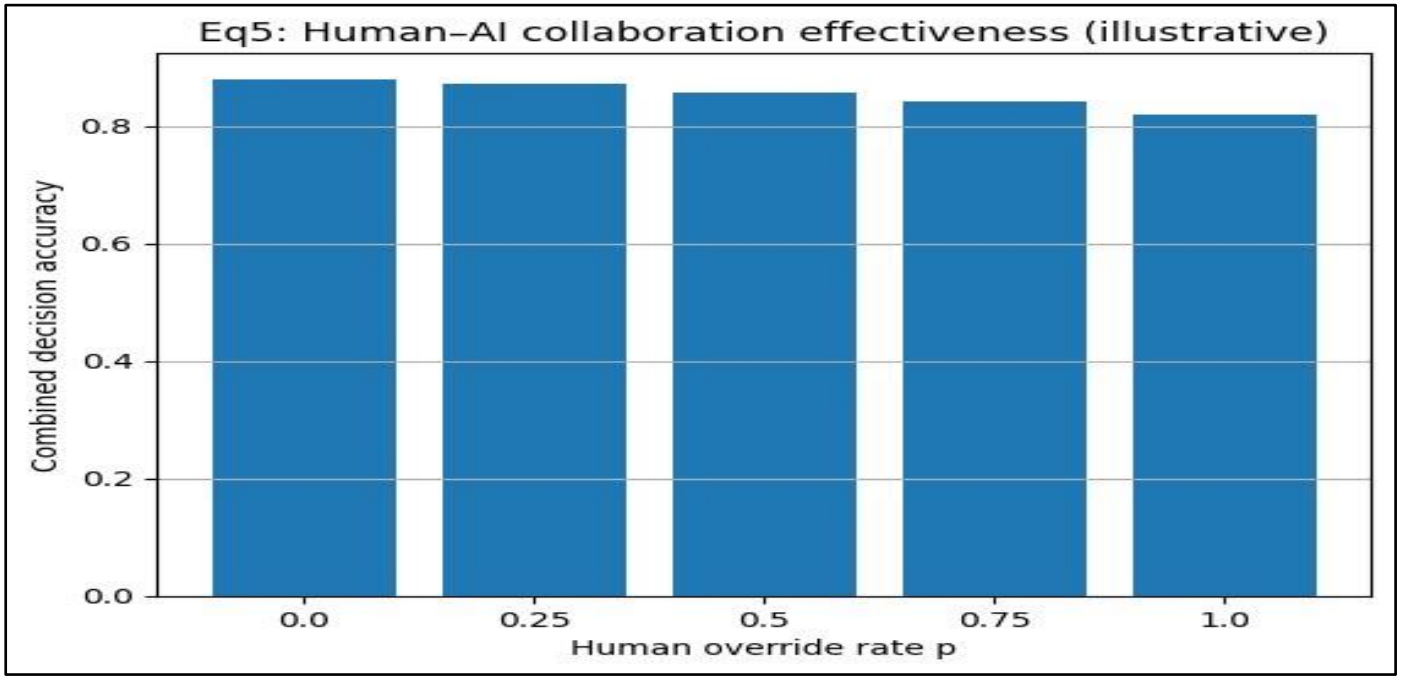

Fig 8 Human-AI Collaboration Effectiveness

- *Equation 5: Human–AI Collaboration Effectiveness*
  Step-by-step derivation (override model)

✓ Let p be probability that a clinician overrides the AI.
✓ Let A_{AI} = accuracy (or utility) when AI decides, A_H when human decides.
✓ Base combined performance:

$$A_{\text{base}}(p) = (1-p)A_{AI} + pA_H$$

✓ Add synergy term (humans are better on edge cases that trigger override):

$$A_{\text{collab}}(p) = (1-p)A_{AI} + pA_H + \beta\, p(1-p)$$

where $\beta \geq 0$ captures complementary strengths (peaks at $p = 0.5$).

Table 3 Calibration Error vs Expected Risk (Human–AI Collaboration Effectiveness)

CalibrationError	ExpectedRisk
0.00	0.0600
0.05	0.0696
0.10	0.0792
0.15	0.0888
0.20	0.0984
0.25	0.1080

VI. IMPLEMENTATION OF STRATEGIES IN HEALTHCARE SETTINGS

Diverse healthcare settings necessitate tailored strategies for leveraging AI. Given the critical importance of reliability, transparency, and compliance in healthcare-related decision-making, implementing risk assessments and mitigation plans capable of covering the entire AI lifecycle is crucial. Establishing dedicated governance structures with defined accountability across technical, operational, and strategic layers enables organizations to identify inherent AI-related risks and work toward their mitigation or containment. The varying nature of AI-related risks is such that organizations commencing their AI deployment journey often focus on simple machine learning applications, while those with advanced capabilities adopt a model risk management approach to comply with evolving guidelines from authorities like the Office of the Comptroller of the Currency.

To address the implementation challenges associated with deploying cloud solutions in healthcare, some organizations consider creating in-house clouds for business units requiring dedicated medical clouds. As demand for AI features increases, their adoption is accompanied by built-in monitoring, evaluation, and continuous improvement mechanisms. Human-centric design approaches and proactive change management strategies for AI adoption also play a role, with dedicated workstreams establishing the required societal trust and acceptance for the deployment of potentially disruptive features.

- *Deployment Architectures and Infrastructure*

Sustainable and responsible AI applications in healthcare must be deployed, integrated, and operated in a manner that supports the stated objectives for sustainability, resource efficiency, and responsibility. Changes to the infrastructure, technology stack, and methods associated with the applications should be employed so that the applications conform to the stated desiderata during their operational phase. Application deployment architecture and infrastructure include AI model and application hosting technologies and systems that substantively support AI-serving operations and should take into account both technical and organizational aspects of deployment. Therefore, they are closely associated with organizational IT operations, which can only be changed if a holistic assessment of the organization is undertaken.

Health services and delivery organizations need to identify intentional design choices relating to the hosting and integration of AI applications that are cognizant of defined sustainability and responsible principles and to select such hosting deployments and integrations as a minimum operating requirement. Support for monitoring and evaluation also needs to be applied, as discussed in Coordination support mechanisms: Monitoring and evaluation. Evaluation of application performance databases can also deliver insights into infrastructure usage by the model and application that can directly influence change and external funding advocacy or requests. The previously identified audit and checkpoint testing committees should be empowered to determine whether the ongoing operation of specific applications is sufficiently resource-efficient, sustainable, and responsible according to the corresponding standards and, if so, initiate and oversee infrastructural change.

- *Monitoring, Evaluation, and Continuous Improvement*

Monitoring and evaluation processes tailored to specific applications and contexts facilitate the ongoing reassessment of the sustainability and responsibility of deployed AI systems. Such processes can provide insights into new and emerging concerns that require attention and remediation, ensuring continual compliance with commitments made prior to deployment, as well as the updating of the underlying models with new data and/or develop new models to address new or different tasks.

Monitoring processes typically incorporate checks on changes in technology, environment, perception, and society, as well as the performance and consequence of the deployed model using metrics defined prior to deployment. The monitoring of a hardware-aware model can also compare the usage and consumption profile with its pre-deployment estimation. Evaluation activities assess the responses observed during the operation of the deployed model against the criteria defined prior to deployment. Ideal evaluation activities look at the performance and potential consequences on multiple specific cohorts and explore deviations from the expected responses learned during the monitoring phase. Both sets of activities support a continuous improvement cycle that reduces the risk and support the stakeholders' expectation, thus avoiding potential reputational damage to the healthcare organisation and its commitment to health equity.

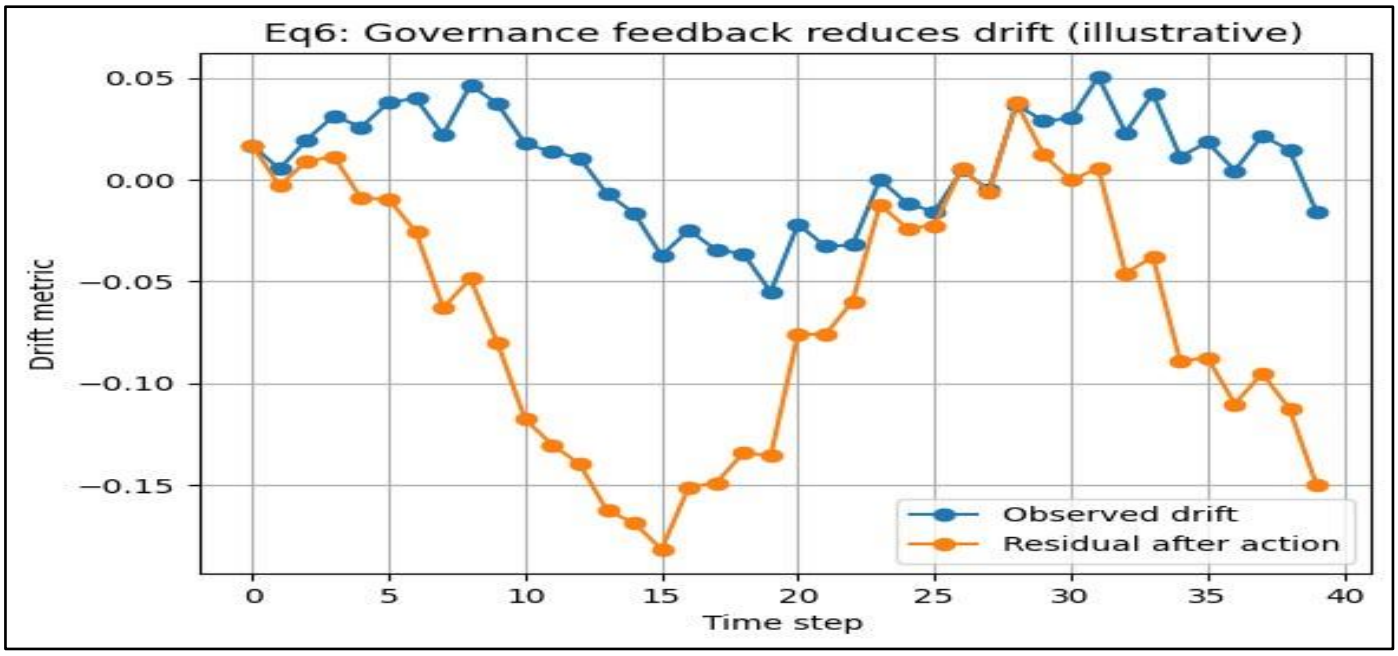

Fig 9 Governance Feedback Reduces Drift

- *Equation 6: Governance Feedback Update*

Step-by-step derivation (feedback control form)

✓ Let m_t be a monitored metric at time t (drift, bias gap, incident rate, energy).
✓ Let target be m^*. Define deviation:

$$e_t = m_t - m^*$$

✓ Let u_t be the governance action (retrain, rollback, threshold change, access-policy change).
✓ A simple proportional update rule:

$$u_{t+1} = u_t - \eta\, e_t$$

where $\eta > 0$ is the governance "gain" (how aggressively you correct).

✓ If the system responds approximately linearly:

$$m_{t+1} \approx m_t + \gamma u_{t+1} + \xi_t$$

(γ effect size, ξ_t noise), then this closes the loop and can reduce drift/bias over time.

➢ *Change Management and Workforce Implications*

Changes to business processes and technology platforms can entail potential challenges and hurdles that may impede successful implementation and execution. Using standard methodologies for program and change management, and established guidance around the deployment of cloud technologies, best practices for adoption of AI may be assessed. It is important to note factors that can facilitate successful pilot testing and operational use of AI systems, even when not all relevant components of the HCD framework are fully addressed.

Many AI systems will necessitate data governance and protection measures that extend beyond typical infrastructure and cloud controls. Commercially available AI products functioning as cloud-hosted managed services will usually have data protection controls (such as encryption, access control, and network security) incorporated into the vendor offering. However, the highly sensitive nature of patient data requires additional consideration. It is common for organisations to establish an AI strategy with the objective of finding a vendor-agnostic technology platform that enables the deployment of multiple AI systems from different vendors but that satisfies the organisation's own data governance principles.

To provide a configure-once-deploy-often platform, organisations may build a data layer that implements data classification at the point of data capture, thereby enabling data to flow through its lifecycle according to the data risk and protection requirements. When configured correctly, this approach to data governance means that the production of the data for AI, the forming of the model, and operational use of the AI outputs are all protected according to the relevant data classification rules both explicitly and transparently without needing AI-specific governance considerations implemented in addition to those already in place for business-as-usual processes.

VII. CONCLUSION

The considerations and recommendations presented contribute to a more principled approach to developing AI technology for healthcare. Demand for AI is growing rapidly, as is the number of actual implementations within hospitals or as standalone products. Nevertheless, there are calls to improve the quality of healthcare AI, requiring more structured dialogue across the entire AI system, not just during the narrow period of algorithm development. Expansion of AI within healthcare presents a huge opportunity for diverse sectors of society. The benefits of AI can be maximised, and unintended consequences

minimised, when deploying solutions sustainably and responsibly.

The environmental and social impacts of AI in healthcare must be actively managed through specific methods, best practices, and institutional changes throughout the S-curve of growth. This will help ensure benefits for society, the environment, users, patients, and other stakeholders. The simple questions posited can guide relevant dialogue within the community and beyond. Addressing them will support the future application and integration of AI in healthcare delivery systems. In the coming years, many healthcare facilities and organisations will deploy operational solutions; AI is set to underpin a substantial portion of the healthcare infrastructure officially, within the sector. It is essential to strive for sustainable and responsible AI implementation that accounts for such considerations during deployment, discusses decisions and related topics, and monitors impacts.

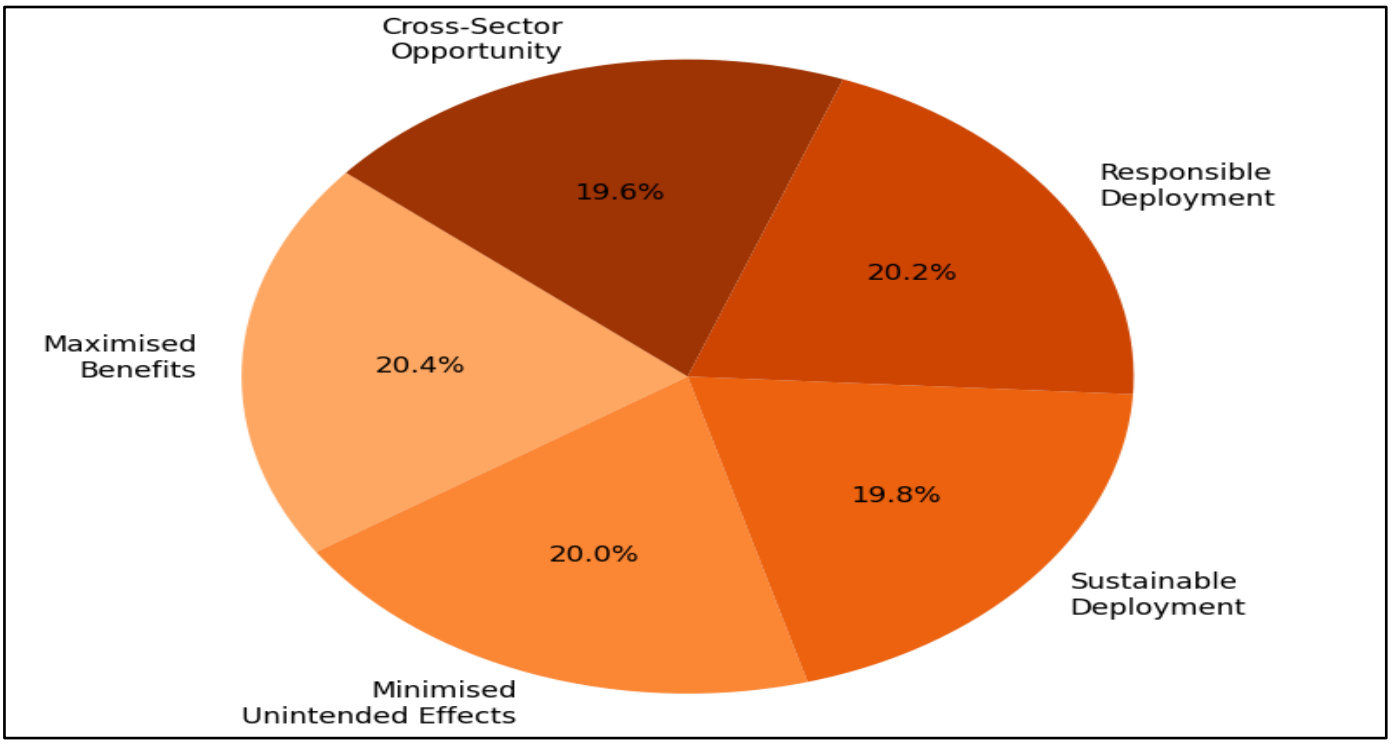

Fig 10 Benefits and Unintended Consequences

➢ *Final Thoughts and Future Directions for Sustainable AI in Healthcare*

Leveraging the benefits of AI in healthcare could enable breakthroughs for patients and the wider population. The development and deployment of AI in this sensitive domain require that social considerations be met, and the technology needs to be sustainable in the narrow and broad sense. Addressing these issues is key to the social acceptance and successful adoption of AI in healthcare. Moreover, since a variety of different AI tools will be needed for real-world deployment, a comprehensive framework for governing AI in its many aspects must also be in place.

Nevertheless, the above discussion can only serve as a starting point, laying down principles and considerations to apply when designing AI for healthcare, rather than offering detailed prescriptions. In practice, the specificities of real-world implementations will necessitate further elaboration of the points made and their application to the chosen use cases. For that purpose, the involvement of the different stakeholders is paramount, be they data donors, patients affected by the disease, or any end-user of AI products. A range of methodologies spanning the lifecycle of AI, from the initial specification of the problem to the deployment of the solution and its integration within the institution or the broader healthcare system, can help ensure that the most salient issues are addressed to the satisfaction of the relevant stakeholders.

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