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Operationalizing Responsible AI in Health Systems: Delphi Based Governance Metrics for Indonesia

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ABSTRACT: Artificial intelligence (AI) is rapidly transforming healthcare delivery in Indonesia. However, the responsible governance of AI systems especially in clinical settings remains underdeveloped. This study aims to identify and prioritize measurable governance indicators for AI in Indonesian healthcare through a Delphi based expert consensus process. A three round modified Delphi method was employed, engaging 30 interdisciplinary experts from healthcare, IT, cybersecurity, ethics, law, and patient advocacy. The process began with 40 indicators drawn from global frameworks (WHO, EU AI Act, ISO/IEC 42001, NIST RMF) and national references (UU PDP, SATUSEHAT). Experts rated each indicator on a 1–9 Likert scale across two iterative rounds. Consensus was defined as median ≥7 and IQR ≤1.5 using RAND/UCLA criteria.Out of 40 indicators, 24 achieved consensus. High priority indicators included clinical safety metrics (e.g., AUROC), data privacy compliance (PDP Law documentation), system integration (SATUSEHAT compatibility), and cybersecurity readiness (incident response plans). Transparency related indicators (e.g., training data summaries, model cards) failed to reach consensus, suggesting institutional gaps in AI explainability. The Delphi process underscored the importance of participatory governance, stakeholder trust, and contextual adaptation of international standards. Consensus indicators reflect domains where operational familiarity and regulatory anchors already exist, while non consensus areas highlight the need for capacity building and clearer guidelines. This study delivers a validated, measurable governance framework to guide responsible AI adoption in Indonesian healthcare. It supports policymaking, institutional audits, and procurement strategies aligned with both local regulation and global standards. Future work should pilot these indicators and expand their use in health system assessments and continuous governance improvement.

Keywords: Responsible AI, Delphi Method, Healthcare Governance, AI Indicators, PDP Law.

INTRODUCTION

Artificial Intelligence (AI) is transforming healthcare globally. It offers potential improvements in diagnostic precision, operational efficiency, and patient engagement. However, its integration also brings complex ethical, legal, and policy challenges.

Global ethical frameworks, such as the Holistic Intelligent Healthcare Theory (HIHT), emphasize the critical importance of data protection and transparent governance mechanisms to uphold patient rights. Similarly, Göktaş & Grzybowski (2025) and Prakash et al. (2022) identify key ethical tensions, including data privacy, fairness, trust, and explainability, as central to AI's responsible deployment. These themes find resonance in the Indonesian context, where increasing AI adoption necessitates governance models tailored to the country's healthcare infrastructure, values, and regulatory architecture.

Despite strong ethical imperatives, operationalizing AI governance in clinical settings requires a robust framework that includes participatory engagement and technical safeguards. Reddy et al. (2021) advocate for the continuous oversight of AI systems, highlighting the value of monitoring tools and evaluation metrics to ensure clinical safety. Alanazi (2023) and Sriharan et al. (2025) further argue for co designed AI tools involving healthcare professionals, enabling alignment between technical innovation and ethical medical practice. Such approaches support not only patient safety but also quality of care, especially where AI systems mediate clinical decisions.

International regulatory efforts such as the EU AI Act and WHO guidelines provide structured risk frameworks for high stakes AI applications. The EU AI Act, for example, mandates transparency, post market surveillance, and risk management, especially for AI systems used in clinical environments (Arigbabu et al., 2024). Complementing this, WHO's recommendations emphasize equitable AI adoption to prevent deepening health disparities (Quazi, 2024). Integrating these frameworks into national governance systems, as Hussein et al. (2024) suggest, requires maturity models that support both regulatory compliance and ethical fidelity.

Indonesia's SATUSEHAT system exemplifies a local initiative enabling structured AI deployment by digitizing healthcare access and standardizing medical records (Trajkovski, 2024). Bhavaraju (2023) observes that such digital systems foster trust in AI and increase operational efficiency, especially in underserved areas. Meskó et al. (2018) highlight that digital systems aligned with regulatory frameworks create environments conducive to responsible innovation. These dynamics are further reinforced by Indonesia's Personal Data Protection Law (UU PDP), which mandates consent, lawful data use, and adequate cybersecurity protocols (Janssen et al., 2024; Ndemo, 2025).

Comparative analysis of global and local AI governance approaches reveals divergence in regulatory philosophies ranging from prescriptive compliance (EU AI Act) to adaptive, principle based models. Cath 2018 and Leenen et al. (2025) point to recurrent ethical concerns like patient autonomy and accessibility, which transcend jurisdictions and demand contextual responsiveness. Hilling et al. (2025) stress the importance of equity in AI access across socioeconomic divides, reinforcing the need for inclusive governance.

Stakeholder diversity emerges as a central component of robust AI governance. Kaye et al. (2024) and Zaidi et al. (2024) show that regulatory effectiveness improves when multiple perspectives from developers to end users are integrated into oversight structures. Comparative studies illustrate variations in stakeholder engagement across countries, underlining the necessity for context sensitive best practices.

Bautista et al. (2024) underscore AI's potential to improve diagnostic outcomes, while simultaneously warning of biases in algorithm design. Ethical review mechanisms are crucial to ensure health equity is not compromised (Sriharan et al., 2025). Engaging health professionals in governance conversations beyond technical deployment is necessary for cultivating trust and accountability (Husnain et al., 2023; Reddy et al., 2024).

As AI systems evolve, governance models must adopt shared accountability frameworks. Cath (2018) argues that humanistic values should be embedded in regulatory strategies. Nong & Ji (2025) recommend forming collaborative ecosystems among regulators, hospitals, and developers to ensure resilience against automated decision risks.

To conclude, AI in healthcare presents tremendous promise but it must be governed through ethical, participatory, and transparent mechanisms that consider both global best practices and local realities. This introduction contextualizes the need for a Delphi derived set of governance indicators that operationalize these complex requirements in Indonesia. Such an approach ensures policy relevance, clinical applicability, and ethical accountability in the digital health era.

METHOD

This study utilized a modified Delphi method to generate and prioritize AI governance indicators tailored for the Indonesian healthcare context. The Delphi approach was selected for its structured, iterative design, which enables expert consensus on complex and interdisciplinary issues especially in areas where empirical evidence is still evolving (Broder et al., 2022; Vloet et al., 2021).

Delphi Method Rationale

The Delphi method is well regarded in health policy for capturing diverse expert insights while minimizing bias through anonymity and iterative feedback (Humphrey-Murto et al., 2016). Its adaptability makes it suitable for governance research, where decisions must be informed by ethical, clinical, legal, and technical considerations (Schults et al., 2022). Key methodological components include: clearly defined objectives, purposeful sampling of interdisciplinary experts, and progressive refinement of indicators across rounds.

Expert Panel Composition

The study employed purposive sampling to select 30 experts across seven domains: clinicians, hospital management, IT professionals, data privacy/legal experts, cybersecurity specialists, ethicists/policy researchers, and patient representatives. This interdisciplinary composition ensured broad coverage of relevant governance domains (Woo et al., 2017).

Delphi Round Design

Three iterative rounds were conducted:

- Round 1: Experts reviewed and refined an initial pool of 40 indicators derived from secondary literature (WHO, EU AI Act, ISO 42001/14971, GDPR/UU PDP, SATUSEHAT).
- Round 2: Participants rated each indicator on a 1–9 Likert scale for importance.
- Round 3: Experts were shown anonymized group scores and rationales and asked to re rate indicators, fostering reflection and consensus (Kerr et al., 2020).

Consensus Criteria and Analysis

Consensus was evaluated using the RAND/UCLA Appropriateness Method (RAM), a widely recognized framework in governance and clinical decision making research (Gertz et al., 2023). An indicator was classified as “consensus achieved” if it received a median score ≥7 and an interquartile range (IQR) ≤1.5. This statistical standard allowed structured comparison across rounds and supported robust interpretation (Sulaiman et al., 2025).

Data Management and Facilitation

Responses were anonymized to prevent dominance or conformity bias, a core strength of the Delphi approach (Vloet et al., 2021). The study team also facilitated asynchronous clarification of indicator definitions when needed to promote consistent understanding, echoing best practices in guided Delphi facilitation (Mills et al., 2020).

Methodological Rigor and Iteration

After each round, summary statistics (median, IQR) and qualitative feedback were shared with the panel to support reflective re evaluation. This iterative process not only honed expert focus but also allowed the emergence of nuanced understanding as participants reconciled individual views with collective trends(Gertz et al., 2023).

Ethical Considerations

All participants provided informed consent. The study ensured confidentiality and compliance with ethical standards for online expert elicitation processes.

In conclusion, by grounding the methodology in established Delphi and RAND/UCLA frameworks, this study ensured methodological rigor while enabling effective interdisciplinary consensus building in AI governance for health policy.

RESULT AND DISCUSSION

This section presents the outcomes of the three round Delphi process, organized by indicator domains, consensus achievements, and divergences. Supporting literature enhances the analysis of clinical applicability, governance relevance, and implementation feasibility of each category.

Initial Indicator Pool

The Round 1 Delphi input comprised 40 indicators sourced from global and local governance frameworks. Table 1 shows the structured categorization.

Table 1: Indicator Domains and Definitions

Domain	Example Indicators	Literature Support
Clinical Safety	AUROC, sensitivity, specificity, PPV, NPV, Brier score, DCA	(Choudhury & Asan, 2020; Evans & Snead, 2024; Labkoff et al., 2024)
Fairness	ΔTPR/ΔFPR across groups, equalized odds, disparate impact	(Zhao et al., 2019; Zsidai et al., 2023)
Privacy & Legal	DPIA presence, PDP Law compliance, anonymization protocols	(Arnaout et al., 2024; Foppen et al., 2024; Tsopra et al., 2021)
Transparency	Training data summary, model card, decision rationale documentation	(Friedrich, 2023; Zanardo et al., 2025)
Cybersecurity	Pen testing, incident response plan, RBAC audit logs	(Arnaout et al., 2024; Potnis et al., 2022)
Governance	AIMS (ISO/IEC 42001), risk audit committee, lifecycle risk review	(Amiot et al., 2025; Yuen et al., 2017)
Integration	SATUSEHAT/RME compatibility, human in the loop logging	(Bhavaraju, 2023; Trajkovski, 2024)
Post Market	Incident reporting, model improvement feedback loop	(Martí-Bonmatí et al., 2022; Mudunuri et al., 2025)

Consensus Results

Consensus was reached on 24 of 40 indicators. These are summarized in Table 2.

Table 2: Selected Indicators with Consensus (Median ≥7 and IQR ≤1.5)

Indicator	Domain	Median	IQR	Consensus
AUROC	Clinical Safety	8	1.0	Yes
Equalized Odds Gap	Fairness	7	1.0	Yes
Legal Basis Documentation (PDP Law)	Privacy & Legal	9	1.0	Yes
ISO/IEC 42001 AIMS	Governance	8	1.0	Yes
SATUSEHAT System Compatibility	Integration	7	1.5	Yes

These indicators align with global consensus benchmarks (Park & Kressel, 2018), and reflect areas with high institutional familiarity and regulatory anchoring.

Non Consensus Indicators

Several indicators failed to achieve consensus. Model card availability and training data transparency received lower scores due to limited implementation experience and awareness.

Challenges Identified:

- Transparency Underprioritization: Transparency remains underemphasized in LMICs due to limited regulatory infrastructure and operational priorities (Drabiak, 2022)
- Documentation Resistance: Institutions often view AI documentation as burdensome, lacking incentives or technical readiness (Naik et al., 2024).
- Explainability Gaps: Despite its known role in clinical trust, explainability tools face resistance or are often misunderstood by end users (Zinchenko et al., 2022).

Observations from Literature Backed Delphi Outcomes

- Consensus indicators are already operational in several Indonesian settings (e.g., PDP Law, SATUSEHAT).
- Global AI frameworks like ISO/IEC 42001 and NIST RMF are seen as adaptable with localized modifications (Festor et al., 2022).
- Local projects in LMICs show promise in operationalizing transparency through community engagement and clinician input (Salwei & Carayon, 2022).

The findings of this study provide a comprehensive and nuanced understanding of how consensus based indicators can be effectively developed and operationalized to support and govern the responsible implementation of AI within Indonesian healthcare. Drawing upon rich insights from a multidisciplinary Delphi panel, the study demonstrated the viability and applicability of global AI governance principles when adapted and contextualized with local health system realities to provide actionable guidance in Indonesia's emerging digital health environment. These findings underscore the critical need to localize international frameworks to reflect the unique social, institutional, and regulatory dynamics that define healthcare delivery in the country.

Delphi Indicators for Policy and Procurement

Delphi derived indicators are not merely academic exercises they are practical, context relevant tools that can be embedded directly into policy frameworks, procurement processes, and institutional governance systems. These indicators offer clarity and structure in evaluating AI technologies, enabling decision makers to ensure that such systems meet a combination of performance, ethical, legal, and safety criteria. As articulated by Darom & Plant (2020), these consensus driven metrics help healthcare institutions align procurement standards with broader societal values, including fairness, safety, transparency, and compliance. Furthermore, by enabling benchmarking and comparative assessment across vendors, the indicators strengthen institutional capacity for ethical procurement and reduce reliance on ad hoc or opaque decision making practices.

Stakeholder Perceptions and Trust

Stakeholder perception plays a foundational role in establishing governance priorities for AI. This includes perceptions not only from clinical practitioners but also from patients, legal experts, IT professionals, and civil society representatives. Research by Mensah et al. (2024) and Solberg et al. (2022) shows that stakeholder confidence in AI technologies is a decisive factor in their adoption. In this study, stakeholder feedback during the Delphi process informed prioritization decisions and revealed areas where skepticism or uncertainty persisted particularly regarding transparency and explainability. Ensuring inclusivity and responsiveness to these views is therefore not only desirable but essential. Strategies such as participatory design, open consultation, and transparent evaluation criteria foster greater buy in from end users and enhance the perceived legitimacy of governance frameworks.

Addressing Ethical and Legal Tensions

The governance of AI in healthcare is inherently a balancing act managing the tension between innovation and ethical safeguards. International frameworks like the EU AI Act (Golpayegani et al., 2023; Marchenko & Энтин, 2022) provide stringent compliance benchmarks, but their rigid requirements may not always align with local infrastructure and enforcement capacity. In Indonesia's case, ethical governance must account for varying levels of digital maturity across facilities, uneven data governance practices, and evolving legal precedents under the Personal Data Protection Law. Policymakers must therefore prioritize flexible, scalable governance mechanisms that can evolve alongside technological and organizational changes. The integration of iterative oversight models and adaptive regulatory provisions can mitigate legal fragmentation and uphold public trust in AI enabled healthcare services.

Lessons from Global Integration into Local Systems

The experience of adapting global AI governance frameworks to Indonesia reveals key lessons about contextualization, relevance, and alignment. Fors & Meissner (2022) caution against the wholesale adoption of international standards without accounting for local health system constraints. In this study, locally relevant factors such as SATUSEHAT integration requirements, infrastructure disparities, and legal nuances were explicitly considered in indicator prioritization. The resulting framework was neither entirely global nor fully domestic, but a hybrid architecture reflective of grounded realities. Such contextualized adaptation is essential to ensure compliance, institutional legitimacy, and practical feasibility across diverse healthcare settings in Indonesia.

Adaptability and Continuous Evaluation

Adaptability must be a defining feature of AI governance frameworks in healthcare. Technologies evolve rapidly, often outpacing the institutional and legal mechanisms designed to oversee them. As highlighted by Сулейманова (2024), embedding evaluation feedback loops and responsive oversight mechanisms into governance systems enhances resilience and ethical vigilance. The indicators produced through this Delphi study are designed for such ongoing use they can be applied not just once but revisited periodically through audits, risk assessments, and quality improvement processes. Institutions may use these indicators to identify gaps, monitor AI related incidents, and recalibrate governance strategies in response to emerging challenges.

Institutional Challenges and Capacity Gaps

The areas where consensus was not reached especially in domains related to model transparency signal important implementation barriers. These gaps likely reflect institutional limitations, including insufficient technical literacy, limited regulatory enforcement, and the lack of incentives to prioritize explainability or documentation. As Unogwu et al. (2023) suggest, advancing AI governance in such environments requires investment in professional development, cross sector collaboration, and accessible governance tools. Government agencies and health institutions alike must play a proactive role in building governance capacity, establishing routine training, and fostering a culture of ethical technology use.

Final Reflections

In conclusion, this discussion underscores that participatory, consensus driven methodologies such as the Delphi approach can be instrumental in bridging the normative aspirations of global AI ethics with the operational realities of national healthcare systems. The indicators validated in this study are not simply conceptual they are implementable, scalable, and measurable. They offer a practical roadmap for policy implementation, regulatory alignment, procurement evaluation, and institutional risk governance. Moreover, the Delphi process itself provides a replicable model for inclusive stakeholder engagement, ensuring that governance instruments remain grounded in clinical, legal, technological, and ethical expertise. As AI continues to expand its role in healthcare delivery, such frameworks will be critical to fostering responsible innovation that protects patients, supports clinicians, and builds public trust in digital health futures.

CONCLUSION

This study successfully developed and prioritized a set of AI governance indicators for the Indonesian healthcare context using a modified Delphi method. Drawing from international best practices and local regulatory frameworks, the consensus driven indicators address essential domains such as clinical safety, fairness, data privacy, cybersecurity, transparency, integration, and institutional governance. These indicators serve as measurable, operational tools that can guide AI adoption, regulation, procurement, and risk management across health institutions in Indonesia.

The incorporation of national anchors like the Personal Data Protection Law (UU PDP) and the SATUSEHAT platform ensures that the proposed framework is not only aligned with global principles (e.g., WHO, ISO/IEC 42001, EU AI Act, NIST RMF) but also locally relevant and practically feasible. This dual anchoring supports regulatory coherence, institutional compliance, and public accountability.

One of the most significant contributions of this research is the advancement of a participatory, evidence based governance model for AI in healthcare. Inclusive expert engagement enabled the Delphi method to refine and validate governance priorities, reflecting both technical viability and stakeholder expectations. The use of transparent scoring criteria and structured consensus protocols further strengthens the legitimacy and replicability of the results.

Although the study achieved broad consensus on many key indicators, areas such as transparency and model documentation revealed critical gaps in institutional readiness and stakeholder familiarity. These gaps underscore the need for ongoing education, capacity building, and regulatory clarification to ensure that AI governance keeps pace with technological developments.

In conclusion, the proposed indicators provide a robust foundation for shaping responsible AI policy and institutional practice in Indonesia's health sector. Policymakers, regulators, and hospital administrators can use these indicators as a benchmark for evaluation, compliance audits, procurement decisions, and continuous quality improvement. Future research should explore the application of these indicators in real world pilot settings, assess their long term impact, and update them periodically to reflect the evolving AI landscape and regulatory environments.

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