

From Healthcare Data to Actionable Intelligence: An Integrative Review and Gated Framework for Trustworthy AI-Enabled Healthcare Analytics

Remon Gameel Ebed Saweris

remongameel@gmail.com

Military Medical Academy

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Abstract

Background: The increasing availability of electronic health records, clinical narratives, biomedical literature, imaging, physiological signals, and patient-generated data has created substantial opportunities for artificial intelligence (AI)-enabled healthcare analytics. Generative artificial intelligence (GenAI) and large language models (LLMs) can extract, summarize, synthesize, and transform heterogeneous healthcare information. However, AI-generated information does not automatically constitute reliable or actionable intelligence. Data quality, interoperability, provenance, hallucination, bias, validation, human oversight, workflow integration, and governance may disrupt the transition from healthcare data to responsible action.

Main body: This integrative review synthesizes recent literature addressing the transformation of heterogeneous healthcare data through AI-enabled analytics and identifies conditions required for reliable and actionable use. A structured literature search was conducted, followed by title and abstract screening and targeted full-text assessment of relevant evidence. Data were organized using a predefined extraction framework covering data characteristics, AI applications, interoperability, provenance, validation, privacy, human oversight, workflow integration, governance, and outcomes. Evidence was synthesized thematically across the healthcare data-to-action pathway. The synthesis identified four interconnected requirements: data readiness, evidence traceability, output reliability, and action readiness. These requirements were integrated into the proposed Data-to-Actionable-Intelligence (D2AI) Gated Framework. The framework conceptualizes healthcare AI as a sequential pathway in which data must first be fit for purpose, generated information must remain traceable to relevant evidence, outputs must undergo task-appropriate validation, and validated insights must be integrated into accountable human workflows before they can become actionable intelligence.

Short conclusion: AI-generated output should not be considered actionable intelligence by default. The D2AI framework provides a health-informatics-oriented model that connects data quality, AI transformation, evidence traceability, validation, human oversight, workflow integration, and governance. It complements existing multidimensional AI evaluation frameworks by emphasizing the sequential conditions required for healthcare information to progress from heterogeneous data to accountable action.

AI, artificial intelligence; D2AI, Data-to-Actionable-Intelligence; EHR, electronic health record; FAIR, findable, accessible, interoperable, and reusable; FHIR, Fast Healthcare Interoperability Resources; GenAI, generative artificial intelligence; LLM, large language model; RAG, retrieval-augmented generation.

1. Background

Healthcare systems increasingly generate large volumes of heterogeneous information through electronic health records, clinical narratives, laboratory systems, medical imaging, biomedical literature, physiological monitoring, and patient-generated data. The growing availability of these data has created opportunities for artificial intelligence (AI)-enabled analytics to support clinical reasoning, operational

management, population health, research, and decision support [1,2,4]. Generative AI and large language models (LLMs) have further expanded these possibilities by enabling extraction, summarization, synthesis, classification, prediction, and natural-language interaction with complex healthcare information [1-5].

Recent reviews demonstrate both the breadth of healthcare AI applications and the persistence of important limitations. GenAI has been investigated across numerous healthcare tasks, while inaccurate or fabricated content, uncertain sources, privacy concerns, bias, and implementation challenges remain recurring concerns [1,5,21]. Recent LLM reviews have similarly emphasized the importance of data, accountability, transparency, ethics, clinical validity, workflow integration, and governance [2-7,19,20]. Evidence from real-world clinical workflows remains comparatively limited, reinforcing the distinction between technical capability and deployment readiness [6].

A central health-informatics problem therefore remains insufficiently organized: how should heterogeneous healthcare data progress through an AI-enabled analytical pathway before the resulting information can appropriately support a real decision or action? Data availability does not necessarily imply data readiness; EHR data-quality research repeatedly identifies completeness, correctness, concordance, plausibility, currency, conformance, and bias as important dimensions [10,11]. Interoperability and semantic consistency are also prerequisites for reliable reuse of heterogeneous clinical information [12-16]. Likewise, an AI-generated output may be fluent or technically accurate without being traceable, validated for the intended task, or integrated into a workflow with clear accountability [17-20,25-27].

Recent multidimensional frameworks have addressed important components of this problem. Ferreira and Rosa organized healthcare LLM evaluation around technical performance, clinical validity, equity, workflow integration, and governance, together with risk-based implementation pathways [7]. Other implementation-oriented frameworks address procurement, integration, monitoring, and evaluation [25], while FUTURE-AI emphasizes fairness, universality, traceability, usability, robustness, and explainability across the AI lifecycle [27]. The present review addresses a complementary question by organizing the pathway itself: the sequential conditions through which healthcare information moves from heterogeneous source data toward accountable action.

The objective of this integrative review was therefore to synthesize recent evidence concerning AI-enabled transformation of healthcare data and to develop a practical gated framework for trustworthy progression from healthcare data to actionable intelligence.

2. Review Objective and Research Questions

The central research question was:

How can heterogeneous healthcare data be transformed through AI-enabled analytics into reliable and actionable intelligence, and what conditions are required to support this transition safely and effectively?

Four subsidiary questions guided the synthesis:

1. What healthcare data characteristics and readiness factors influence AI-enabled analytics? 2. How are AI systems used to transform, extract, synthesize, or reason over healthcare data? 3. What mechanisms are required to establish traceability and reliability of AI-generated outputs? 4. What human, workflow, governance, and monitoring conditions are required before AI-derived insights can become actionable intelligence?

3. Methods

An integrative review design was selected because the objective was conceptual integration across heterogeneous evidence domains rather than exhaustive mapping or quantitative estimation of the literature. The review focused on peer-reviewed literature concerning AI-enabled healthcare analytics, with particular attention to the transformation of heterogeneous healthcare data into clinically or operationally actionable information.

A structured literature search was conducted to identify relevant evidence published primarily from 2020 to 2026. The preliminary PubMed strategy combined three concept blocks: AI/GenAI/LLMs; healthcare; and analytics/decision support. The core strategy was:

("artificial intelligence"[Title/Abstract] OR "generative artificial intelligence"[Title/Abstract] OR "generative AI"[Title/Abstract] OR "large language model*"[Title/Abstract] OR LLM[Title/Abstract] OR "foundation model*"[Title/Abstract])

AND

(healthcare[Title/Abstract] OR "health care"[Title/Abstract] OR clinical[Title/Abstract] OR hospital*[Title/Abstract] OR medical[Title/Abstract] OR patient*[Title/Abstract])

AND

(analytics[Title/Abstract] OR "healthcare analytics"[Title/Abstract] OR "clinical analytics"[Title/Abstract] OR "clinical decision support"[Title/Abstract] OR "decision support"[Title/Abstract] OR "data analysis"[Title/Abstract] OR "actionable intelligence"[Title/Abstract]).

Eligible evidence addressed AI, GenAI, or LLMs in healthcare; transformation or interpretation of healthcare data; clinical or operational decision support; data quality, provenance, interoperability, privacy, validation, or governance when directly linked to AI-enabled analytics; and human oversight or workflow integration. Evidence focused exclusively on non-healthcare AI, purely technical AI without a healthcare relationship, drug discovery without relevance to the data-to-intelligence pathway, health professions education, or commentaries lacking substantive evidence or conceptual contribution was excluded.

Retrieved records were screened at the title and abstract level, followed by targeted full-text assessment of potentially relevant studies. Data were extracted using a predefined framework covering author/year, study type, AI type, data type, data problem, AI application, interoperability, privacy, validation, human

oversight, governance, outcomes, key limitations, and framework components. Findings were synthesized thematically across the data-to-action pathway. [19,20]

The search and synthesis strategy was designed to support conceptual integration rather than exhaustive estimation of the literature volume. Accordingly, the review does not report PRISMA-style study-flow counts or pooled quantitative estimates.

4. Thematic Synthesis

4.1 Healthcare Data and Data Readiness

Healthcare AI systems inherit important characteristics of their source data. Missingness, inconsistency, heterogeneous representations, limited interoperability, temporal incompleteness, coding variation, and inadequate representativeness can affect downstream analytics. Data readiness therefore extends beyond data availability and asks whether the available data are fit for the intended analytical task. [8].

4.2 AI-Enabled Transformation

AI systems can transform healthcare information through extraction, integration, summarization, classification, prediction, semantic normalization, and generation. LLMs are particularly relevant to unstructured clinical narratives and multimodal or text-rich workflows. However, transformation can introduce context loss, unsupported inference, or task mismatch. Model capability should therefore be considered separately from deployment readiness. [9].

Recent comprehensive reviews of healthcare RAG similarly emphasize retrieval design, evaluation, factual consistency, and governance as determinants of reliability [35].

4.3 Evidence Traceability

Traceability concerns whether an AI-generated statement, recommendation, or summary can be connected to identifiable and verifiable source evidence. Relevant mechanisms include data provenance, source attribution, retrieval grounding, evidence verification, auditability, and versioning. Traceability improves the ability to inspect and challenge outputs, but traceable does not mean correct.

For medical imaging AI, CLAIM similarly emphasizes transparent reporting sufficient to assess rigor, reproducibility, and generalizability [31].

For predictive models, PROBAST provides a structured approach to assessing risk of bias and applicability [32].

4.4 Output Reliability

AI outputs require task-appropriate assessment of accuracy, robustness, hallucination, omission, bias, clinical validity, external validity, safety, and reproducibility. Benchmark performance alone may not

establish reliability in a specific healthcare setting. Reliability is therefore treated as a gate between generated information and potential use. [22-24].

Early-stage clinical evaluation of AI decision-support systems should be reported with attention to human factors, safety, and clinical context [29].

For clinical trials involving AI interventions, the CONSORT-AI extension provides additional reporting expectations intended to improve transparency and reproducibility [30].

Automation bias is a recognized human-factors risk in clinical decision support and supports the need for explicit human oversight and accountability [33].

Human evaluation of healthcare LLMs remains important, while standardization of evaluation methods is still developing [34].

4.5 From Validated Insight to Actionable Intelligence

A validated insight becomes actionable only when it is relevant to a real decision, integrated into an appropriate workflow, assigned to a responsible decision-maker, and supported by meaningful human oversight and escalation or override mechanisms. Human oversight should include sufficient epistemic and cognitive capacity, decision authority, intervention capability, and accountability.

4.6 Cross-Cutting Governance

Privacy, security, equity, bias management, accountability, regulation, auditability, and continuous monitoring cut across every stage. Governance is therefore represented as a cross-cutting layer rather than a final step. [22-24,28].

5. D2AI Gated Framework

The proposed Data-to-Actionable-Intelligence (D2AI) Gated Framework models healthcare AI as a sequential pathway: Figure 1 summarizes the proposed pathway and the four gate conditions.

Healthcare Data → Gate 1 Data Readiness → AI-Enabled Transformation → Gate 2 Evidence Traceability → Gate 3 Output Reliability → Gate 4 Action Readiness → Actionable Intelligence → Decision/Action → Outcome → Continuous Monitoring.

Gate 1—Data Readiness asks whether available healthcare data are sufficiently fit for the intended analytical task. Requirements include accuracy, completeness, consistency, validity, timeliness, representativeness, interoperability, and linkability. Failure should trigger remediation and reassessment.

Gate 2—Evidence Traceability asks whether generated information can be traced to identifiable and verifiable healthcare evidence. Relevant requirements include provenance, source attribution, retrieval grounding, evidence verification, auditability, and versioning.

Gate 3—Output Reliability asks whether an AI-generated output is sufficiently accurate, robust, safe, valid, and reproducible for its intended use. Hallucination, omission, bias, poor generalizability, and inadequate external validation represent potential failure conditions.

Gate 4—Action Readiness asks whether the validated insight can be safely incorporated into a real decision or action. Requirements include meaningful human oversight, decision authority, workflow integration, escalation, override mechanisms, and accountability.

The framework deliberately distinguishes three states: Generated Output $\neq$ Validated Insight $\neq$ Actionable Intelligence. It also distinguishes Traceable $\neq$ Correct and Model Capability $\neq$ Deployment Readiness $\neq$ Action Readiness.

The D2AI framework is intended as a complementary framework rather than a replacement for existing multidimensional evaluation and governance models [7,25,27]. Its principal contribution is the sequencing and gating of established requirements along a health-informatics-oriented data-to-action pathway.

6. Operational Definition of Actionable Intelligence

For the purposes of this review, actionable intelligence refers to healthcare information derived through an AI-enabled analytical process that has sufficient evidentiary traceability, task-appropriate validation, contextual relevance, and workflow integration to support an accountable decision or action. Figure 2 summarizes the conceptual distinction between generated output, validated insight, and actionable intelligence.

This definition intentionally distinguishes actionable intelligence from AI-generated content. An output may be fluent, informative, or even factually correct without being actionable if its evidence cannot be established, its reliability has not been assessed for the intended task, or no appropriate workflow and decision authority exist for acting upon it.

Accordingly, actionability is treated as a system-level property rather than a model-level performance characteristic.

7. Positioning Relative to Recent Frameworks

Recent literature has increasingly moved beyond model-centric assessment of healthcare artificial intelligence toward multidimensional evaluation incorporating clinical validity, equity, workflow integration, human factors, and governance. Recent reviews have also examined the broad applications and challenges of generative AI and large language models in healthcare.

Most recently, Ferreira and Rosa proposed a multidimensional framework encompassing technical performance, clinical validity, equity, workflow integration, and governance, together with risk-based implementation pathways. Their review provides an important evaluation-oriented perspective on

responsible healthcare LLM deployment. The present framework addresses a complementary question. Rather than primarily organizing the dimensions by which an AI application should be evaluated, the D2AI framework organizes the healthcare data-to-action pathway according to sequential conditions that should be satisfied before information progresses from one state to the next.

Specifically, D2AI distinguishes four transitions: Data Readiness → Evidence Traceability → Output Reliability → Action Readiness. This organization integrates requirements that are often addressed separately across health informatics, AI evaluation, data quality, clinical workflow, and governance literature. The proposed contribution is therefore not the introduction of entirely new risk categories, but the integration and sequencing of established requirements into a data-to-actionable-intelligence pathway.

The framework emphasizes that an AI-generated output should not be considered actionable intelligence solely because it is fluent, accurate on a benchmark, or technically validated. Actionability requires successful progression through data, evidence, reliability, and workflow gates. The framework consequently complements existing multidimensional evaluation and governance models by providing a health-informatics-oriented representation of how healthcare information progresses from heterogeneous data toward accountable action.

8. Practical Implementation

The D2AI framework can be operationalized as a staged implementation checklist. First, organizations should define the intended decision or action and then determine whether the source data are fit for that purpose. Second, AI transformation should be configured with explicit provenance and traceability requirements. Third, outputs should undergo task-specific validation before routine use. Fourth, validated insights should be integrated into workflows with clear responsibility, escalation, override, and documentation mechanisms. Finally, performance and safety should be monitored continuously after deployment. Table 1 summarizes the evidence-informed dimensions, while Table 2 lists common failure modes and corresponding mitigations.

This sequence can support implementation across clinical decision support, operational analytics, population health, revenue-cycle analytics, patient communication, and research workflows. The framework is not intended to prescribe a single AI technology or model architecture. Instead, it provides a decision-oriented structure for assessing whether an AI-enabled information pathway is sufficiently mature to support action.

9. Research and Implementation Implications

For health informatics practice, D2AI suggests that AI governance should begin before model selection and extend through data preparation, evidence traceability, validation, workflow integration, and post-deployment monitoring. For researchers, the framework highlights the need to report not only model

performance but also data readiness, provenance, intended-use context, human oversight, and implementation conditions.

Future studies should test D2AI prospectively in real healthcare environments and determine whether gate-based assessment improves safety, reliability, implementation quality, or decision outcomes. Empirical work is also needed to operationalize measurable thresholds for each gate and to evaluate how thresholds should vary according to risk, clinical context, and organizational capacity.

10. Limitations

This review has several limitations. First, the synthesis was designed for conceptual integration rather than exhaustive quantitative mapping of the literature; therefore, it should not be interpreted as a systematic estimate of all available evidence. Second, the literature is evolving rapidly, particularly for GenAI and LLM applications, and relevant evidence may emerge after the search period. Third, heterogeneous study designs and outcome definitions limit direct comparison across studies. Fourth, the D2AI gates represent an evidence-informed conceptual synthesis and require prospective empirical validation before they can be interpreted as validated implementation criteria. Finally, the framework is deliberately health-informatics oriented and may require adaptation for highly specialized domains.

11. Conclusion

AI-enabled healthcare analytics can transform heterogeneous healthcare data into potentially valuable information, but the transition from data to action is not automatic. The D2AI framework proposes four sequential gates—Data Readiness, Evidence Traceability, Output Reliability, and Action Readiness—through which healthcare information should progress before it is treated as actionable intelligence. The framework complements existing multidimensional evaluation and governance models by emphasizing the sequence and dependencies between data quality, AI transformation, evidence, validation, workflow, human oversight, and accountability. Future empirical studies should test and operationalize the framework in real-world healthcare settings.

Declarations

Ethics approval and consent to participate

Not applicable. This review used published literature and did not involve human participants, identifiable human data, or animal subjects.

Consent for publication

Not applicable.

Availability of data and materials

No datasets were generated or analysed during the current study. The evidence synthesized in this review was obtained from publicly available published literature.

Competing interests

The author declares that he has no competing interests.

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Authors' contributions

RS conceived the review, developed the research questions and conceptual framework, conducted the literature synthesis, drafted the manuscript, and approved the final version.

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Use of generative AI

Generative AI tools were used to support language refinement, structural organization, and drafting assistance during manuscript preparation. The author reviewed, verified, and takes responsibility for the accuracy, interpretation, and final content of the manuscript.

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Tables

Table 1. Evidence-informed dimensions of the D2AI gated framework.

Dimension	Core question	Key requirements	Failure consequence
Data Readiness	Are healthcare data sufficiently fit for the intended analytical task?	Accuracy; completeness; consistency; validity; timeliness; representativeness; interoperability; linkability	Remediate and reassess
AI Transformation	Can relevant healthcare information be transformed without unacceptable loss or distortion?	Extraction; integration; summarization; classification; prediction; normalization; reasoning; generation	Reconfigure task/model or reassess
Evidence Traceability	Can generated information be traced to identifiable and verifiable evidence?	Provenance; source attribution; retrieval grounding; verification; auditability; versioning	Do not advance to reliability gate
Output Reliability	Is the output sufficiently accurate, robust, safe and valid for intended use?	Accuracy; hallucination; omission; bias; robustness; clinical validity; external validation; reproducibility	Validate, restrict, or reject use
Action Readiness	Can the validated insight be safely incorporated into an accountable workflow?	Human oversight; decision authority; workflow integration; escalation; override; accountability	Do not operationalize
Continuous Monitoring	Does performance and safety remain acceptable after deployment?	Drift detection; incident monitoring; audit; revalidation; feedback	Intervene, recalibrate, or suspend

Table 2. Common failure modes across the healthcare data-to-intelligence pathway.

Stage	Potential failure mode	Illustrative problem	Principal mitigation
Data	Missingness/inconsistency	Incomplete or conflicting records	Data-quality profiling and remediation
Data	Heterogeneity/poor interoperability	Different coding, formats, or identifiers	Semantic normalization and interoperability controls
Data	Poor representativeness	Training or input data do not reflect intended population	Representativeness assessment and subgroup analysis
Transformation	Context loss/task mismatch	AI transformation omits clinically important context	Task-specific testing and domain review
Evidence	Poor provenance	Sources cannot be identified or verified	Provenance capture and source attribution
Evidence	Unsupported generation	Output is not grounded in available evidence	Retrieval/grounding plus verification
Reliability	Hallucination/omission	Plausible but incorrect or incomplete output	Task-specific validation and safety checks
Reliability	Bias/limited generalizability	Performance varies across populations or settings	External validation and equity assessment
Workflow	Automation bias	Users over-rely on AI output	Meaningful human oversight and override
Action	Unclear responsibility	No clear decision authority	Explicit accountability and escalation
Monitoring	Silent degradation	Performance changes after deployment	Continuous monitoring and revalidation

Table 3. Conceptual positioning of the D2AI framework relative to recent healthcare AI reviews/frameworks.

Source	Main contribution	Primary orientation	Relationship to D2AI
Moulaei et al., 2024 [1]	Applications, benefits and challenges of GenAI	Application landscape	Provides background on GenAI capabilities and limitations
He et al., 2025 [2]	Data, technology, applications, accountability and ethics	Healthcare LLM landscape	Supports data and governance dimensions
Lin & Kuo, 2025 [3]	LLM applications and clinical integration	Clinical/technical integration	Supports transformation and human-workflow dimensions
Zhou et al., 2025 [4]	Applications, technical challenges and ethics	Biomedical/healthcare LLM landscape	Supports privacy, bias and workflow concerns
Ghnemat & Saleh, 2026 [5]	Clinical AI applications and risks	Clinical AI evaluation	Supports reliability and governance dimensions
Artsi et al., 2025 [6]	Real-world clinical implementation	Workflow implementation	Supports action readiness and monitoring
Ferreira & Rosa, 2026 [7]	Multidimensional evaluation and governance	Evaluation/governance	Closest conceptual comparator
Xie et al., 2025 [8]	Automated EHR data-quality rule generation	Data quality	Provides empirical support for data readiness
D2AI	Sequential data-to-action pathway	Health informatics + AI implementation	Integrates and sequences these requirements into four gates

Figures

Figure 1. The D2AI gated pathway from heterogeneous healthcare data to actionable intelligence

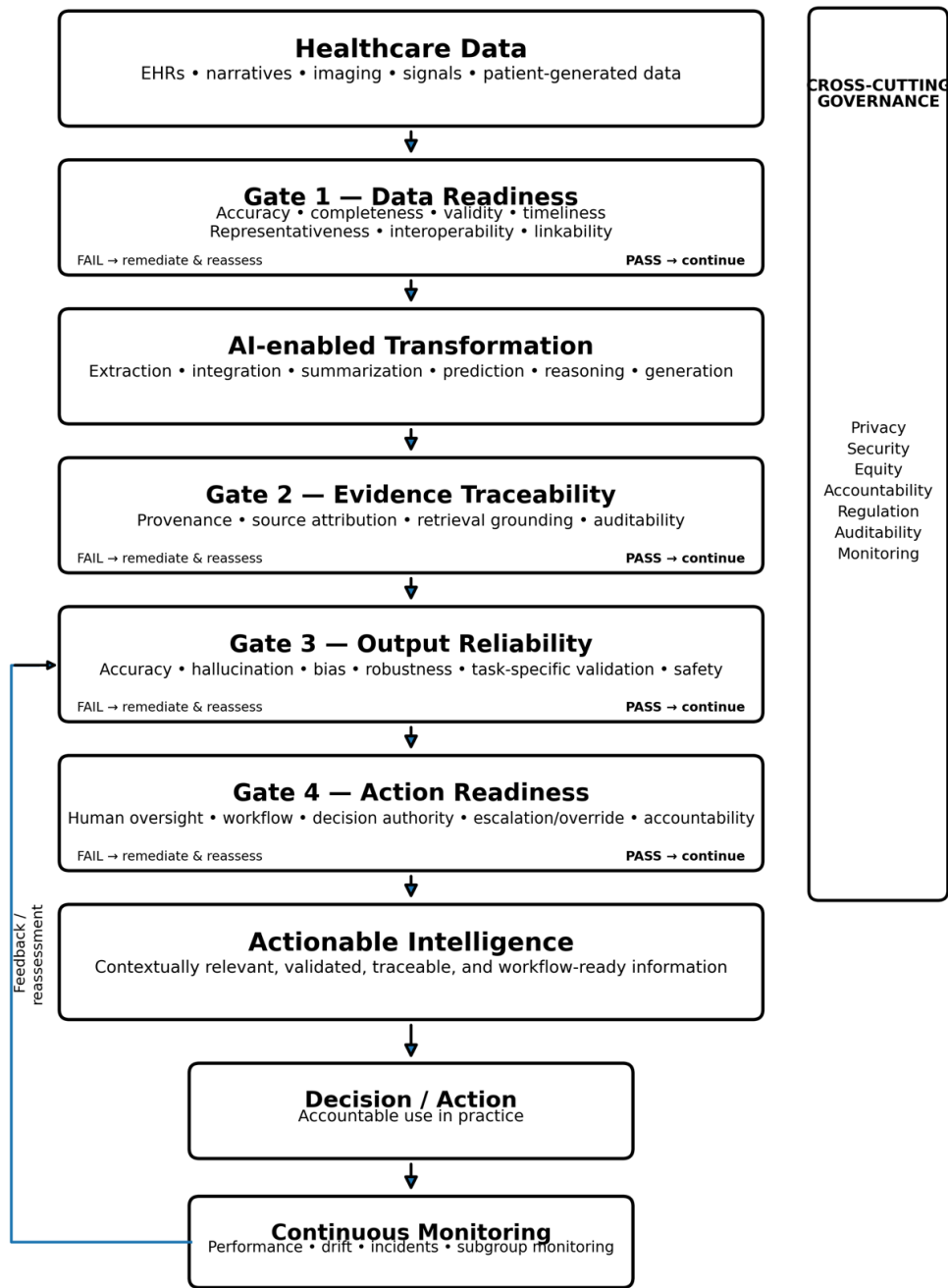


Figure 1

The D2AI gated pathway from heterogeneous healthcare data to actionable intelligence. The pathway proceeds from healthcare data through four sequential gates: Data Readiness, Evidence Traceability, Output Reliability, and Action Readiness. Each gate requires a pass condition before progression; failure triggers remediation and reassessment. Privacy, security, equity, accountability, regulation, auditability, and monitoring operate as cross-cutting governance requirements.

Figure 2. Conceptual distinction between AI-generated output, validated insight, and actionable intelligence

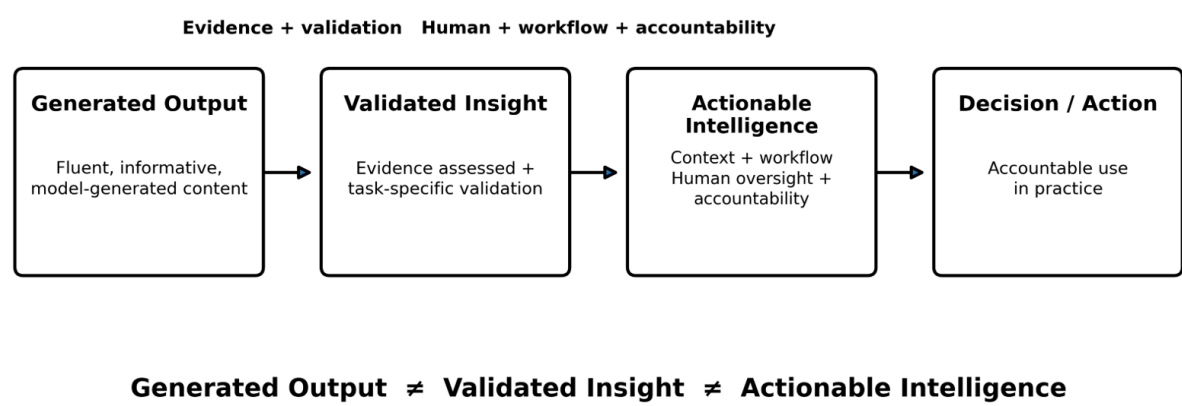


Figure 2

Conceptual distinction between AI-generated output, validated insight, and actionable intelligence. AI-generated output becomes a validated insight only after appropriate evidence assessment and task-specific validation. A validated insight becomes actionable intelligence only when contextual relevance, meaningful human oversight, workflow integration, decision authority, and accountability are present.