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Transparent Intelligence Explainability Frameworks for AI-Driven Clinical Decision Support in Healthcare Business Intelligence

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ABSTRACT: Healthcare business intelligence (BI) enhances decision-making through evidence synthesis, visualization, and communication. New technologies and techniques introduce machine learning-based solutions that augment workflows and produce clinical insights (e.g. risk scores, disease progression predictions). However, such insights are notoriously opaque and fail to come with explanations. There are objective reasons why clinical stakeholders may reject insights that lack explainability: clinician trust directly affects decision-making performance, clinicians are trained to be safety vigilant, and AI-based support for decision-making processes is crucial in many use-cases. BI solutions that generate insights not only for clinicians but also for patients must also support patient understanding to be clinically meaningful. Decision workflows integrate clinical insights into user-facing systems.

Accordingly, requirements for explainability apply to such solutions. Insufficiently transparent clinical insights and recommendations may lead to errors, waste resources, harm the credibility of the systems or healthcare more broadly, and ultimately harm patients. Recent studies show that unexplained clinical insights adversely affect clinician trust and decision-making performance, warning of potential negative repercussions when integrating untrusted AI-generated insights into clinical workflows. Support for reproducible clinical BI roadmap—covering model provenance, version control, explainability measures, importance of real-world monitoring, support for automated explanation generation at scale, and integration with clinical governance and workflow—may also help limit undesired consequences with AI-based clinical BI solutions.

KEYWORDS : Explainable AI; Artificial Intelligence; Machine Learning; Healthcare; Business Intelligence; Clinical Decision Support; Transparency; Explainability; Availability; Interpretability; Clinical Governance Explainable AI;

I. INTRODUCTION

The proliferation of artificial intelligence (AI) in healthcare holds great promise for improving clinical decision-making and patient outcomes. Yet, while research effort on clinically relevant AI systems seems boundless, the tangible benefits remain limited. One important reason is the opacity of AI-generated insights: the models driving clinical predictions, risk assessments, or treatment recommendations are often considered black-boxes, with no straightforward way for users to understand how clinical decisions are derived or the rationale behind them. An increasing body of literature indicates that explainable AI helps build the clinician trust critical for acceptance, safety, and performance. Inadequate explanations also elevate the risk of undetected bias—arguably the most prevalent failure mode of AI systems.

To mitigate the dangers of black-box AI, clinical insights from BI projects should not merely be presented in visually attractive widely, as analysts might wish; they should be generated in ways that promote confidence among the decision-makers who ultimately implement the guidance. Several evidence-based principles can underpin such explainability. They draw on the established discussion on explaining AI models, extend it to the specific domain of healthcare BI, and take a step beyond pure explainability of the AI workings towards the more tangible goal of facilitating clinical decision-making within a safe and robust framework for patient outcomes.

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To mitigate the dangers of black-box AI, clinical insights from business intelligence (BI) projects must be designed not merely for visual appeal, but for epistemic trust, clinical relevance, and accountable use. Evidence-based principles of explainability emphasize that explanations should be purpose-driven, aligning with specific clinical questions rather than generic model transparency. Explanations should be clinically grounded, linking model outputs to familiar medical concepts, pathways, and risk factors so that clinicians can contextualize results within existing knowledge. They must also be actionable, clearly indicating how an insight can inform diagnosis, treatment selection, or monitoring, rather than only describing statistical associations. Beyond technical interpretability, effective explainability in healthcare BI requires uncertainty communication, traceability of data sources, and validation against real-world outcomes, enabling decision-makers to assess reliability and limitations. By shifting the focus from simply exposing algorithmic mechanics to supporting meaningful clinical reasoning, explainable BI systems can foster confidence, reduce unintended harm, and embed AI-driven insights within a safe, transparent, and outcome-oriented framework for patient care.

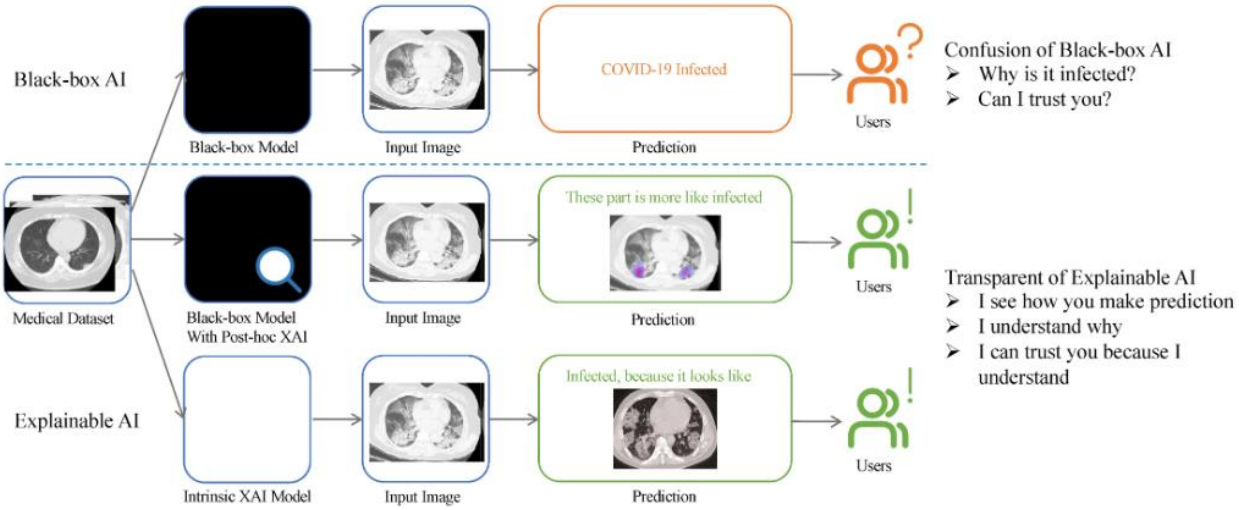

Fig 1: Explainable AI Techniques in Healthcare

1.1. Background and Significance

Business intelligence (BI) collects and analyzes structured data from multiple sources to improve decision-making. Dashboards synthesize data into visualizations that guide strategic and operational choices, often for clinical, financial, and operational efficiency. One key area is healthcare analytics, a BI application that analyzes patient, clinical, and institutional data to improve patient and population outcomes. Increasingly, healthcare analytics relies on artificial intelligence (AI) models. Evidence shows that workforce management AI can improve scheduling, patient outreach, and patient–physician matching.

However, even as transparency becomes a critical requirement in many domains, the clinical groundwork within which these AI-generated clinical insights and recommendations reside is often merely a tabulated signal without supporting provenance, versioning, documentation, or decision-relevant explainability. The resulting lack of explainability is particularly troubling because clinical personnel must trust and act on these AI-generated signals to enhance patient care and safety. Explainability is therefore an essential property of these AI-generated insights and recommendations, with ramifications for clinician engagement, safety, performance, and, in turn, patient safety and treatment outcomes. So although it is imperative that clinical personnel be involved in the development of these systems, the transparency burden cannot rest solely with those personnel. Instead, those signals with the potential for high risk and high impact should have a supporting explainability framework that facilitates clinician understanding, engagement, and safe application.

Equation 1: Binary risk prediction as a probability (logistic model)

Let features for patient ibe $x_i \in \mathbb{R}^d$, weights $w \in \mathbb{R}^d$, bias b.

Step 1: linear score (log-odds)

$$z_i = w^\top x_i + b$$

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Step 2: map score to probability (sigmoid)

$$\hat{p}_i = \sigma(z_i) = \frac{1}{1 + e^{-z_i}}$$

Step 3: decision threshold (alert / positive prediction)

$$\hat{y}_i = \begin{cases} 1 & \text{if } \hat{p}_i \geq \tau \\ 0 & \text{if } \hat{p}_i < \tau \end{cases}$$

1.2. Research design

Explainability in AI-generated clinical insights is explored using published insights from a sample of models, AI User Experience design, and guidance on clinical BBI created by the author and collaborators. Collected evidence identifies AI-generated clinical insights and assessed explainability for breadth and rigor. The assessment framework documents how explainability supports transparency and the perception and impact of AI-generated clinical insights, especially for patient interactions. Explainability encompasses documentation of data, AI models, and AI pipelines to support trust, decision support systems, and higher-level explanations at the clinical Governance Board. Evidence and related research highlight the provision of high-level, low-effort explanation within easy reach of key stakeholders, especially the clinical data consumer and clinical decision maker.

The BI system evaluates clinical acute coronary syndrome and other conditions; identify individual and location-based Biostatistics; and generate clinical alerts and non-automatic, assailable recommendations for rectification. The ACSSSHBF conduct reenactment and simulation on a large scale. The BI4COVLRT evaluates a 12-component clinical BBI at requested frequencies; provides alerts; highlights at-risk groups; and recommend risk-reduction strategies for designated governance with assurable effect on services. As AI-powered insight generation and explanation become standard, an empirical foundation for understanding the role, perception, and impact of explainability is timely.

II. FOUNDATIONS OF EXPLAINABLE AI IN HEALTHCARE

Explainability is concerned with making components of a system or decision understandable, and has gained renewed prominence in the field of Artificial Intelligence (AI) because of concerns surrounding the opacity of deep learning solutions. Transparency in data, models and evidence is thus essential to explainability in Clinical AI. Explainability for AI-generated patients insights and recommendations in Healthcare Business Intelligence (BI) is an emerging area of interest because BI synthesizes extensive, real-time clinical data into operational and strategic insights that observe the principles of the Learning Healthcare System (LHS). The objective is to ensure that Business Intelligence dashboards containing Clinical AI developments, insights and recommendations are usable by clinicians. Applications laid out in a scope of Healthcare Business Intelligence revolve around the synthesis of data from traditional Electronic Health Records (EHR) and other sources.

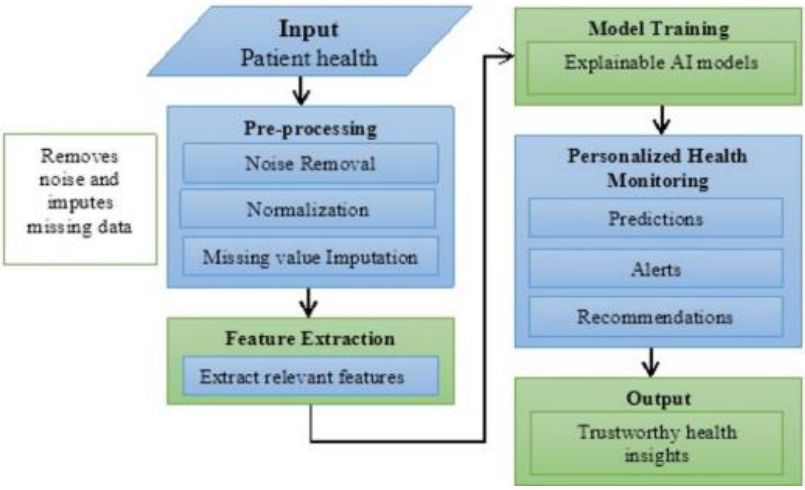

Fig 2: Foundations of Explainable AI in Healthcare

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The first stage of characterising explainability is to define into the four concepts of explainability, interpretability, transparency and accountability. A Healthcare BI system that incorporates clinical-domain models, explanations and recommendations provides an ideal test-bed for this depth of understanding as it integrates large-scale observational Clinical AI with the governance and technical criteria of the Learning Healthcare System, yet is delivered in the familiar formats of BI dashboards. The research framework for Health Business Intelligence that covers these concepts is also described, along with the definitions for key supportive components of data pipelines, dashboards, recommendation workflows, clinical governance, and integration with Clinical data registries and other instructional sources, to ensure clarity and completeness of the explanation-centric approach.

2.1. Definitions and Scope

Explainability refers to the degree to which a human can understand the reason for a decision. Interpretation is the degree to which a human can understand the rationale for predictions or recommendations made by an artificial intelligence (AI) model. Transparency, in turn, refers to the design of an AI model, whereas accountability refers to the accountabilities put in place to respond to an AI model's outcome. In the context of business intelligence (BI) for healthcare, explainability considers assurance mechanisms from all players in the environment producing clinical insights and recommendations.

The focus of explainability in healthcare BI is on AI models that are black-boxes for which there is no human-oriented interpretation of the prediction or recommendation. It encompasses any method that enables a human to interpret or understand important aspects of the produced decision support. Business Intelligence refers to an environment that supports management decision processes through data and analytics. It is a view, collection of models, and collection of applications that provide situational awareness of the operation of a business using an integrated store of historical data that have been processed to support decision-making. Applications of explainability in healthcare BI are limited to the generation of clinical insights and the suggested actions taken from the insights, and not so much focused on the decision-making process itself.

Equation 2: Discrimination (how well the model separates outcomes)

For true labels $y \in \{0,1\}$and predictions $\hat{y}$:

- **TP**: $y = 1, \hat{y} = 1$
- **FP**: $y = 0, \hat{y} = 1$
- **TN**: $y = 0, \hat{y} = 0$
- **FN**: $y = 1, \hat{y} = 0$

From these:

$$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}, \mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{FP} + \mathrm{TN}}$$

ROC traces $(\mathrm{FPR}(\tau), \mathrm{TPR}(\tau))$as τvaries from 1 down to 0.

Algorithm

1. Sort patients by score $\hat{p}_i$descending.
2. Sweep a threshold across sorted scores.
3. After each distinct score, compute TP, FP → compute TPR, FPR.
4. Plot TPR vs FPR.

If ROC points are $(\mathrm{FPR}_k, \mathrm{TPR}_k)$sorted by increasing FPR:

$$\mathrm{AUC} = \int_0^1 \mathrm{TPR}(\mathrm{FPR})\, \mathrm{d}(\mathrm{FPR}) \approx \sum_{k=1}^{K-1} \frac{\mathrm{TPR}_{k+1} + \mathrm{TPR}_k}{2} (\mathrm{FPR}_{k+1} - \mathrm{FPR}_k)$$

2.2. Key Concepts in Healthcare BI

Health BI comprises applications that rely on AI to generate insights for managers, administrators, policymakers, and the general public rather than for clinicians making direct patient-care decisions. Healthcare BI data pipelines encompass ETL or ELT processes combined with exploratory data analysis that precedes model deployment. Transformed data are typically presented in dashboards and other visual formats, such as interactive data exploration

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tools. The presented insights can serve as direct input to decision workflows followed by managers or other nonclinical stakeholders, such as clinical governance committees and operational oversight boards. These workflows can also be more flexible and serve as decision-support tools to aid policy and management decisions at levels that span departments and even jurisdictions.

Much of the discussion thus far has focused on the technical and research modelling aspects of AI decision pipelines supporting the clinician in making decisions about the care of specific patients. However, similar approaches apply within the larger bureaucratic context of healthcare, where managers, policymakers, and other nonclinical personnel use insights generated by AI within business-intelligence platforms. These insights are not applied directly as input to high-stakes decisions involving patient health but provide or inform input to less-consequential advisory or governance processes. Recent discussions have highlighted the need for explainability in AI applications supporting decision processes. Although such need was anticipated and supported by various stakeholders (e.g., Garvian et al. 2022), real-world evidence suggests that explainability is not being addressed in practice (Liaw et al. 2023).

III. DATA, MODELS, AND EVIDENCE IN HEALTHCARE AI

AI relies heavily on data, yet the quality of health data is often questioned. Stakeholders view data problems as an underlying risk of AI deployment in clinical settings. High-stakes settings require that data used to develop AI applications meet high standards, following Aifred Health's summary of Faber et al. (2020). Data quality dimensions encompass lineage, completeness, bias, timeliness, privacy, and governance. Provenance, including data sources, transformations, and pipelines, must be captured. When multiple datasets inform a model, issues of data alignment, harmonization processes, merit, and provenance become critical. External data acquisition must undergo strict privacy and data-sharing governance; incomplete or missing data should be evaluated for predictive impact during model training or validation. Finally, the data used to fuel clinical AI must be suitable for validating its predictions, especially with regard to bias and lag. Provenance records, metadata, and documentation play a key role in assuring data quality and are part of the explainable AI framework.

AI methods can gain a performance advantage when applied to real-world clinical decision-support tasks with suitable format, volume, and quality. The need for explainability and interpretability must, however, be closely matched to the use case, the end users, and the consequences of predictions. For divergence from existing clinical practices, and especially for alerting, high-stakes use cases may require tests for human performance—using experimental and validation data that closely reflect real-world prover—before AI predictions can be trusted. In these settings, performance metrics for discrimination, calibration, and fairness should be complemented by suitable criteria for interpretability and explainability.

3.1. Data Quality and Provenance

Data quality and provenance are vital elements of explainable AI in healthcare BI because they underpin the integrity, reliability, and trustworthiness of data analytics and visualizations. Poor-quality data compromise valid insights and, consequently, clinician trust in the entire information pipeline. Concerns about lineage, completeness, bias, timeliness, privacy, and governance need to be addressed during the exploratory phase of application development. Documenting data preparation and harmonization lays the groundwork for the interpretability of clinical models.

The provenance of BI data used in clinical AI must be carefully scrutinized. Sources for severity scores (e.g., measures of the extent or harm done) and for queries on model completenes) are critical. BI information needs not just to originate from authoritative sources (e.g., EHRs, treatment guidelines, disease registries) but also to be complete and timely. Guidelines for completeness and bias, established in the 2021 Guide to the Good Use of Data, should be applied. An additional dimension—privacy—becomes much more sensitive when the solutions are used in patient care. Solutions in production need a governance model, especially when they include machine learning or presume the potential creation of algorithms.

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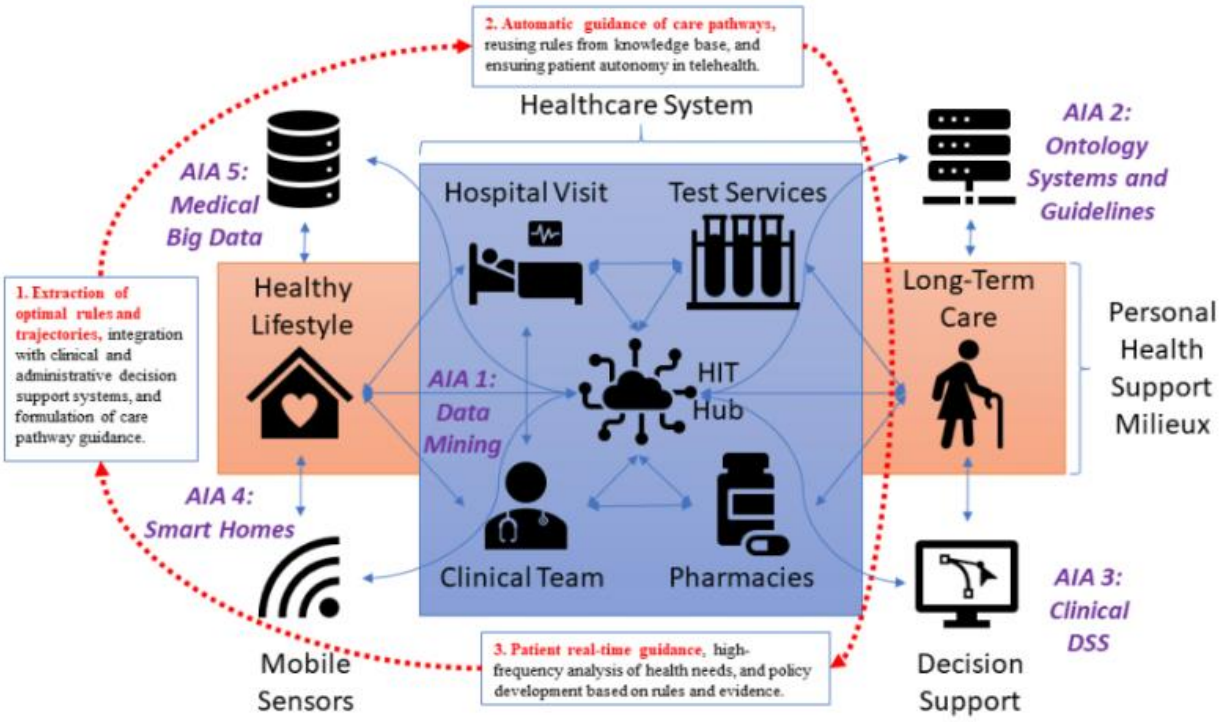

Fig 3: Data Quality and Provenance of Explainable AI

3.2. Model Selection and Evaluation Metrics

The choice of learning algorithms for healthcare applications is informed by the nature of the target prediction problem: whether the outcome is continuous, categorical, or ordinal; whether the objective is risk prediction, diagnosis, triage, or prognosis; whether treatment effect heterogeneity is considered; and whether less common events require methods that are robust to class imbalance. The performance of a prediction model is typically assessed using discrimination (i.e., the ability to distinguish between different outcome classes), calibration (i.e., the correspondence between predicted risk and observed risk), and fairness (i.e., the equity of risk across population groups). Additional evaluation criteria can provide further confidence in the deployment of clinical prediction models; common choices are transparency, robustness to distributional shift, and computational efficiency. Some applications and stakeholders also require the ability to interpret or explain the model predictions. Indeed, interpretability is a key factor in model selection for BI solutions that generate clinical insights or recommendations, particularly for supervised models that inform clinical decision tasks such as diagnosis, therapy selection, or disease management. Interpretability and explainability criteria can also inform the selection of ensemble methods, where the base learners need not be wholly interpretable.

The area of explainable AI (xAI) has produced a wide range of literature describing methods for examining the logic behind a model's predictions. Concepts such as feature importance, surrogate models, rule-based systems, counterfactual explanations, and narrative explanations can assist clinicians in understanding the prediction and thereby help to fulfil the crucial requirement of supporting – rather than replacing – clinical decision making.

Equation 3: Calibration (are predicted probabilities numerically correct?)

Split predicted probabilities into bins B_m(e.g., 0–0.1, 0.1–0.2, …).

For each bin m:

- Mean prediction:

$$\bar{p}_m = \frac{1}{|B_m|} \sum_{i \in B_m} \hat{p}_i$$

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- Observed event rate:

$$\bar{y}_m = \frac{1}{|B_m|}\sum_{i \in B_m} y_i$$

$$\text{Brier} = \frac{1}{n}\sum_{i=1}^{n}(\hat{p}_i - y_i)^2$$

Step-by-step expansion:

$$(\hat{p}_i - y_i)^2 = \hat{p}_i^2 - 2\hat{p}_i y_i + y_i^2$$

Since $y_i \in \{0,1\} \Rightarrow y_i^2 = y_i$, so:

$$\text{Brier} = \frac{1}{n}\sum_{i=1}^{n}(\hat{p}_i^2 - 2\hat{p}_i y_i + y_i)$$

IV. TECHNIQUES FOR EXPLAINABILITY IN CLINICAL AI

Explainability is both a foundation of Explainable AI and a consequence of trustworthy systems. In the healthcare domain, the research, innovation, and delivery of patient care can all be advanced by AI systems. However, these systems must be trustworthy, and a key precondition for trust is explainability. Ideally, not only the clinical and patient-specific outputs of the AI systems but also the data and models must be understandable to healthcare stakeholders.

Key stakeholders rely on AI systems at different times during the clinical governance process. Clinicians and system developers make decisions about data quality for training, testing, and integrating the AI systems. Clinicians involved in providing patient care and support roles are concerned with the correctness and safety of clinical insights. Consequently, the explainability requirements associated with these different roles and uses differ.

The explainability techniques considered in this section support two aspects of AI-generated healthcare data and insights. First, AI-generated models should be inherently interpretable or, if this is not possible, post hoc explanations should be generated that lead to clear, accurate, and usable explanations of the model output. Second, the clinical insights and recommendations derived through these models should use narrative and visual means to ensure that they contribute directly to the decisions made in real time for individual patients.

The explainability techniques considered in this section address two complementary dimensions of AI-generated healthcare data and insights: model-level transparency and clinically actionable communication. On the model side, priority is given to approaches that are inherently interpretable—such as transparent architectures or constrained models whose internal logic can be readily understood by clinicians—while also acknowledging that highly complex models may require robust post hoc explanation methods. These explanations must move beyond abstract technical descriptions and instead provide clear, accurate, and context-aware rationales that illuminate how specific inputs influence outputs, including uncertainty and limitations. On the clinical side, insights and recommendations produced by AI systems should be translated into intuitive narrative summaries and well-designed visualizations that align with clinical workflows. By presenting explanations in forms that are concise, relevant, and patient-specific, these techniques ensure that AI outputs are not merely informative but directly support real-time clinical reasoning, shared decision-making, and trust in AI-assisted care.

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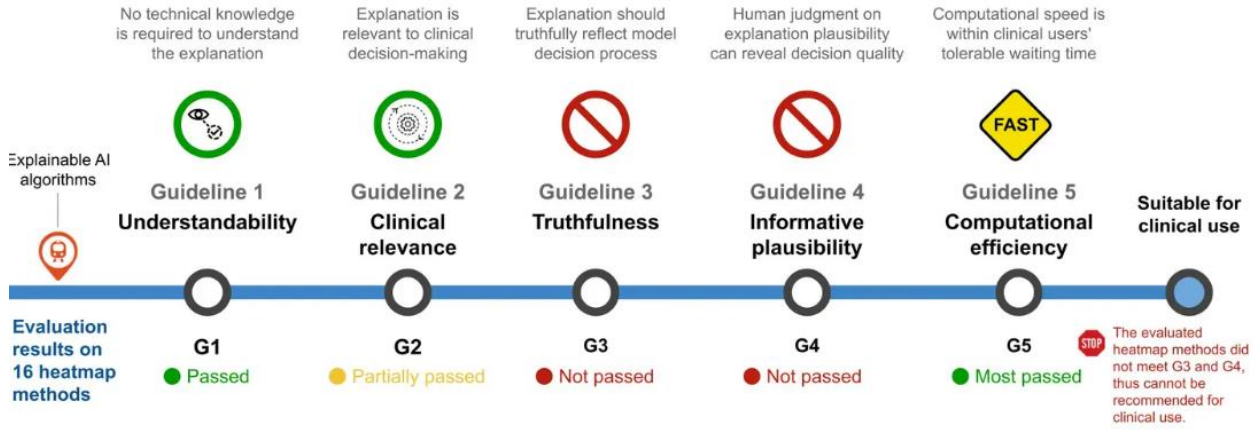

Fig 4: Guidelines and Evaluation for Clinical Explainable AI

4.1. Interpretable Models and Post Hoc Explanations

Several design choices enhance an AI system's ability to explain its predictions and underlying processes. Wherever appropriate, the models in clinical BI applications should be readily interpretable. Popular interpretable models include linear predictors, decision trees, rules, and certain types of neural networks. If an interpretable model cannot deliver sufficient predictive performance, the use of a more complex black-box model should be complemented by a post hoc explanation. Both explanation techniques inform end-users about reasons for the model prediction.

A common approach involves training a simpler (often linear) surrogate model that mimics a more complex black-box model on the predictions of that model (the "teacher"). Surrogate explanations typically identify influential features but do not necessarily shed light on the interplay among the features. Techniques such as Shapley additivity, Shapley interaction values and LM explainers help with this. Visualizations of feature importance can also aid explainability. For example, the absolute values of the gradients of the prediction with respect to each feature can show which features influence the prediction most, whether positively or negatively. This visualization technique is particularly suited for neural networks. Further explanation about the trained model can be provided using methods like rule-based reasoning or counterfactuals.

4.2. Visualization and Narrative Explanations

AU: Actionable visualizations, explanations integrated with clinical workflows, and patient-specific narratives that explain and support decisions enhance AI in Healthcare Business Intelligence (BI).

Effective visualization supports healthcare professionals engaged in complex decision-making or interpreting model predictions. Dashboards and BI tools graphically depict multivariate relationships, drawing attention to important elements and possible changes. These visualizations also enable joint human–AI decision-making. Decision support systems provide additional, more specific AI-generated insights on next steps. Unlike dashboards, which present information for general consideration or exploration, decision support systems convey information essential to optimize decisions. To maximize trust and utility, such insights should be aligned with clinicians' existing workflows. Automatic alerts—derived primarily from external process models or human expertise—add supplemental guidance on important issues requiring immediate attention.

Narrative explanations further improve utility and acceptance of AI in BI applications. Language generation models (e.g., OpenAI's GPT- 3) raised the possibility of creating narratives that recount everything needed for an explicit human decision. These models support end-to-end narratives for model predictions—but not necessarily in a way that optimally serves the underlying decision. For example, such an AI-generated narrative could state that an explanation is "not available" because the use of a neural network does not provide sufficient insight. Improved narratives replace simply stating predictions with presenting recommended decisions and the rationale for these decisions—thereby supporting and explaining the clinical decision. Narratives that summarize the data and AI's decision rationale further boost confidence in the recommendation and enable clinicians to validate predictions during the clinical workflow.

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Equation 4: Fairness (equity across groups)

$$P(\hat{y} = 1 \mid A = 0) = P(\hat{y} = 1 \mid A = 1)$$

A simple disparity measure:

$$\Delta_{DP} = \mid P(\hat{y} = 1 \mid A = 1) - P(\hat{y} = 1 \mid A = 0) \mid$$

$$P(\hat{y} = 1 \mid y = 1, A = 0) = P(\hat{y} = 1 \mid y = 1, A = 1)$$

Disparity:

$$\Delta_{EO} = \mid TPR_{A=1} - TPR_{A=0} \mid$$

Requires both:

$$TPR_{A=0} = TPR_{A=1} \text{and} FPR_{A=0} = FPR_{A=1}$$

V. TRANSPARENCY IN AI-GENERATED CLINICAL INSIGHTS

Explainability enhances clinician trust, required for safe, reliable, and efficient use of clinical insights from Artificial Intelligence. Clinicians must understand and accept the AI-generated guidance they receive, yet many widely used techniques for achieving explainability are not fit for purpose. AI-generated insights should include information about the AI system used, support integration with clinical decision-support systems and alerting, and enable external stakeholders to assess the potential for harm and benefit.

Clinician trust in clinical AI systems is a prerequisite for their reliable and safe use. When clinicians do not trust the AI's insights, they may ignore the recommendations or adjust the insights communicated to them, or they may over-rely on them and cease to apply their clinical judgment. All three responses may expose patients to harm. Given the limitations of existing AI models—especially when evaluated in the real-world settings for which they were not explicitly developed—clinicians should not, and do not, trust AI systems blindly. They should instead understand both the systemic and patient-specific reasons behind a clinical AI system's insights and be able to consider them calibratively, as they would any other clinical decision-support tool.

The integration of an AI system into clinical decision-support systems and alerting workflows is one means of addressing clinician trust and calibration. Existing systems for clinical decision support and alerting are designed to ensure that the information and workflows they present are aligned with the clinical journey taken by a patient. Incorporating AI-generated insights into these systems makes them more familiar and natural for clinicians to engage with and thus lowers the cognitive barriers to use. Integrating AI insights with established clinical decision-support systems additionally has the potential to improve clinician oversight of clinical AI systems. Rather than blindly following a recommendation, a clinician can review the guidance alongside any other information, clinical judgment, or other insights from supporting systems that may be relevant to the specific patient."

Equation 5: Shapley values (SHAP) — step-by-step definition
Shapley value for feature j:

$$\phi_j = \sum_{S \subseteq N \setminus \{j\}} \frac{\mid S \mid ! \, (d - \mid S \mid - 1)!}{d!} [v(S \cup \{j\}) - v(S)]$$

Step-by-step meaning

1. Consider every subset Sthat does **not** include j
2. Compute the **marginal contribution** of adding j: $v(S \cup \{j\}) - v(S)$
3. Weight that contribution by the number of orderings in which Sprecedes j
4. Sum over all such S

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Additivity property

$$f(x) \approx \phi_0 + \sum_{j=1}^{d} \phi_j$$

5.1. Trust, Explainability, and Clinical Decision Support

The relationship between explainability, clinician trust, and clinical performance has important implications for AI-generated clinical insights. Trust in a clinical decision-support tool improves when the reason for a recommendation can be easily grasped (99), and a lack of trust may lead clinicians to disregard a recommendation even when it would increase patient safety (100). Therefore, there are risks to patient safety if an algorithm in a clinical decision-support tool is not explainable, because the clinician cannot judge whether the recommendation is sensible or not. Alert fatigue, the premature dismissal of clinical alerts due to their frequency or perceived irrelevance, also affects patient safety (101), and integrating explanations into alerts has been identified as a way to mitigate alert fatigue (102). Finally, decision-support tools are most effective when the recommendation aligns with the decision flow, as it allows information to be processed in an intuitive and natural manner (103). Indeed, applying methods that fit within the normal clinical decision process has been identified as a key to leveraging machine learning to improve healthcare (101).

The low levels of explainability and explicit validation of clinical AI have serious safety implications (39). Clinical decision-support warnings that lack proper clinical validation reduce clinician trust, with evidence linking low trust to increased risk of clinical error (100). If the role of explainability is to enable clinical validation of recommendations, the absence of explanations must likewise lead to reduced trust and higher risk of error. Should an alerting system trigger a non-intuitive recommendation—an absence of alert fatigue—the recommendation must still be easy to trust for it to be followed.

Table: Data provenance table (schema)

Field	Meaning
Data source	EHR system / registry / guideline source
Time window	dates included
Cohort definition	inclusion/exclusion logic
Transformations	ETL/ELT steps, units, harmonization
Missingness	per-feature missing rate, handling
Bias checks	subgroup coverage, label leakage checks
Governance	approvals, access controls

5.2. Documentation, Reproducibility, and Auditability

Requirements for the documentation and transparency of all AI systems are well-established (e.g., Microsoft Research 2018). For clinical AI, these include provenance records delineating the data, model, analytic environment, relevant code, and human contributions; versioning of models, code, and data; model cards that detail the purpose, training, evaluation, and fairness of a model; model-specific data sheets that characterize the data used to train and evaluate it; reproducible templates to ensure that any dataset can be reliably prepared for model training and evaluation, and a pipeline that ensures that all these components are linked and thus easily accessible during an audit.

Provenance records should specify the (supervised or unsupervised) data pipelines used to prepare training, validation, and testing datasets, documenting data completeness, potential biases, and unit checking. Model cards should indicate the main performance metrics used to evaluate the quality of calibration and fairness, the training completion status, and the main hyperparameter settings, practices of infrastructures and users present during data collection and handling, and whether these are expected to influence the decisions to be made based on the predictions. Model- and data-specific sheets should summarize the achievability of model performance, the main potential uses of the models with appropriate interpretation of the predictions, as well as the scope of the model fitness for purpose.

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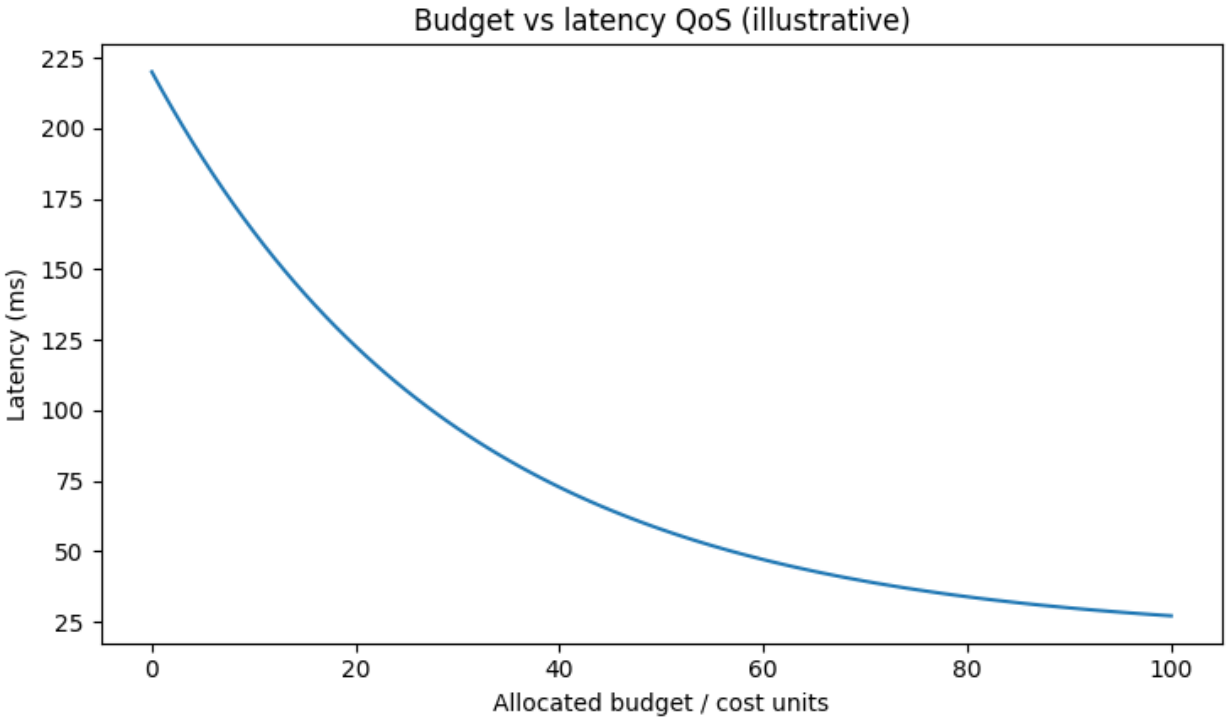

VI. CONCLUSION

As healthcare organizations increasingly deploy AI models on real-world data, more attention is being focused on validating their impact on care quality and efficiency. Explainability is an important pillar of this investigation. Clinical decisions supported or informed by opaque AI-driven insights may be biased toward greater reliance on computerized evaluations, making human oversight more prone to error when discrepancies arise and limiting the potential for education and knowledge transfer. Such effects may compromise clinician trust in AI and contribute to an observed increase in error rates when alerts from clinical decision support systems are ignored or rejected. Transparency in the generation of model-based clinical insights can mitigate these risks and has therefore been nominated as one of the important criteria for assessing the degree of explainability.

Transparency is essential to ensuring that AI-generated clinical insights are understood, scrutinized, and trusted by healthcare professionals. Progress in defining the conditions required for transparency has been made using insights from related domains such as software engineering and safety-critical systems. Five key areas have now been identified, encompassing the documentation and reproducibility of the models generating AI-based clinical insights. Integrating these insights with existing clinical governance frameworks for AI is likely to reduce the risk of AI-induced clinical errors and bias while supporting the use of AI to enhance clinician knowledge and the quality of care. The approach also aligns with the broader objectives of patient safety and the promotion of efficient and effective healthcare delivery.

6.1. Future Trends

Healthcare BI systems capable of generating clinically relevant insights and recommendations can enhance clinical decision support workflows and alert mechanisms. Nevertheless, end-user explainability is critical to ensure clinician trust, validate AI-enhanced safety, and improve actual clinical performance. AI-generated clinical insights that diverge from base-rate expectations may be particularly problematic, even when such divergence constitutes an appropriate clinical action. Explainability can be especially impactful in these circumstances. For instance, failure-to-rescue predictions that understandably addressed non-ventilated patients during a time when such patients were at particularly high risk helped avert potential patient safety issues and improve clinician satisfaction. Furthermore, explainability needs to extend beyond the details underpinning the underlying clinical AI model and encompass the explainability of any workflows or systems that utilize the AI model. Supplementary end-user deliverables that explain how the clinical workflow and alert integrate AI model predictions into the decision support process therefore enhance explainability.

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The growing pressure to demonstrate that AI-based products, services, and systems improve outcomes for patients, health professionals, and the health system at large remains an AI industry imperative, particularly for clinical AI applications. Such evaluations must be undertaken through real-world validation studies in active hospital settings. Beyond simple trust-issues associated with AI technologies, incrementally explainable products, services, and systems for clinical AI that allow clinicians to grow their trust in the output of AI products in a flexible manner can provide a practical roadmap for transparent, reproducible, and auditable AI technologies in healthcare for the foreseeable future. Transparent, reproducible, and auditable AI technologies for healthcare will eventually receive higher-level regulatory and industry endorsement. Standardized and official support for enabling transparency of AI explanations, lineage of explainable AI products, and reproducibility of clinical AI technologies have started to emerge. Further development in these areas will foster widespread adoption of such conceptually simple yet powerful and widely applicable transparency principles for AI technologies across clinical applications.

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