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Trustworthy Intelligence: Interpretability of Predictive Models in Clinical Decision Support

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Abstract:

At the heart of this is AI/ML technology which has disrupted the healthcare industry with their predictive algorithm-based models that can now diagnose diseases, predict patient outcomes and recommend treatment pathways. Yet, applications of these technologies in clinical use rely on the interpretation of their decision making. This paper investigates the role of interpretability in trustworthiness of AI in Clinical Decision Support Systems (CDSS). We also emphasize two main goals: (1) to review the interpretability methods used for supervised learning models in healthcare, and (2) to introduce a framework for making interpretability consistent among value for clinical practice, regulations, and ethics. Based on the recent literature, case examples and empirical validation, this research presents the trade-offs between model accuracy and transparency and demonstrates how explainable models build clinical trust, aid in patient outcomes and assist in compliance. Our guideline framework blends intrinsic and post-hoc interpretability tools, specifically for different healthcare applications, which serves as a roadmap to ensure the responsible use of AI in medicine.

Keywords: Explainable AI, Clinical Decision Support Systems, Supervised Learning, Interpretability, Trustworthy AI, Healthcare Machine Learning, Medical Ethics, Regulatory Compliance

1. Introduction

The introduction of artificial intelligence (AI) and machine learning (ML) into the medical field represents an important step forward in the way administrative and clinical decisions will be made within healthcare systems. Prediction algorithms are currently available for early disease diagnosis, personalized treatment decisions, outcome prediction, and allocation of resources. However such models are frequently more accurate although their practical use is hampered by a common problem: lack of interpretability.

In high-stakes areas such as healthcare, where actions directly affect the lives of patients, it is insufficient for a model to be accurate: it also has to be interpretable. Caregivers are morally as well as legally bound to their decisions, so there is any explanation provided in human terms for the results given back by artificial intelligence. This demand for visibility is not only a technical one; it's also inherently linked to trust, accountability, and legal compliance.

Interpretability in AI is the ability to explain how a a model arrives at a given output, so the decision-making process can be made transparent to users. In the context of supervised models, specially in Clinical Decision Support Systems (CDSS), interpretability is what drives whether prediction outputs will be trusted or disputed and consequently implemented in clinical practice.

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In this paper, we examine the role of interpretable AI in enabling trusted intelligence in healthcare. 2. We will organize our exploration around two goals:

To review the interpretability methods implemented on supervised learning models in a health scenario, both intrinsic models (e.g., logistic regression, decision trees) and post-hoc explanation tools (e.g., SHAP, LIME).

To suggest a framework by which to reflect interpretable strategies into a range of clinical application, including technical generalization, ethical aspects, and conformation to the recent guidelines such as GDPR, HIPAA, and AI-based medical device regulation of US FDA.

2. Literature Review

2.1 AI Experiences in Healthcare

AI applications to healthcare have proliferated rapidly over the last decade, and supervised learning models have provided the basis for clinical prediction. From the diagnostic aids in radiology as well as pathology to the risk stratification in cardiology and oncology, such models have demonstrated the ability of surpassing the statistical models by a great degree. However, many of these models are the so-called "black box" providing no explanation of how the inputs are translated to the outputs. This obscurity can represent a barrier to their acceptance in clinical environments in which there is a strong emphasis on clinical responsibility.

2.2 Interpretability: Definitions and Dimensions

Interpretability is simply the degree to which a human can grasp why a decision was made. At least Doshi-Velez and Kim (2017) make a clear distinction between these three observations: what they call simulatability (how well can a human simulate the model), decomposability (understanding each element), and algorithmic transparency (knowledge about the learning process). These dimensions frame the interpretability methods as they may be applied to healthcare.

2.3 Intrinsically Interpretable Models

These are the transparent-by-design models. Examples include:

• Logistic Regression: A widely employed model in disease risk prediction and the magnitude of each feature is the relative weight of features.

• Decision Trees: Question stems that give clear decisions rules and are frequently employed in diagnostic instruments.

• Rule-based systems: provide rules that emulate clinical judgements, which are generally very intuitive.

Although these models are popular for their interpretability, however, they are not as competitive as sophisticated algorithms such as a neural network.

2.4 Post-Hoc Interpretability Techniques

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To make complex models transparent, various post-hoc methods were introduced:

• LIME (Local Interpretable Model-agnostic Explanations): Produces locally faithful explanations for each prediction.

• SHAP (SHapley Additive exPlanations): Fair feature importance based on cooperative game theory.

• Grad-CAM and saliency maps: Visual techniques used in image-based ML methods.

• Counterfactual Explanations: Demonstrate how differences in input change the prediction, helpful for "what-if" analyses.

They allow explanation without changing the black-box model, but the explanation can sometimes be inconsistent or very high level to provide clinical interpretation.

2.5 Related Work on Interpret- able CDSS

Some prominent works have been devoted to explainable models in the context of CDSS:

• The eICU Collaborative Research Database has been used for analysis of interpretable models for mortality prediction.

• IBM Watson employed rule-based systems in its early versions for oncology care recommendations.

• Related work in sepsis prediction has incorporated SHAP explanations into hospital dashboards and has increased trust and adoption in clinicians [7].

2.6 Challenges and Gaps

Despite increasing interest, there remain several practical challenges:

• The absence of standardized interpretability quantification metrics

• Minimal participation of the clinician in model validation

• No clear definition of what constitutes a "sufficient" explanation (in the draft rules).

• Tension between model naturalness and interpretability and model accuracy.

Addressing these challenges necessitate a framework that institutionalizes interpretability in the context of medical objectives—this is also, the void that this paper seeks to fill.

3. Methodology and Evaluation

3.1 Research Design

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In order to investigate interpretability in clinical decision support for supervised learning, to the best of our knowledge, this study applies the following methods in a multiple methods study:

• Systematics literature review for interpretability tools used in healthcare.

• Comparative investigation of models in terms of the trade-off in interpretability and accuracy.

• Analytical framework informed by case study and regulation.

Technical performance and clinical value Evaluate: The evaluation will focus on both technical performance and clinical relevance, so that the models come up with interpretability methods that are not only statistically valid, but also practically usable in real hospitals.

3.2 Dataset Selection Criteria

For model validation we find datasets with the following characteristics to:

• Real-world medical data are based on clinical data repositories (e.g., MIMIC-III, eICU Collaborative Database).

• Structured patient data (vital signs, lab tests, and demographics) incorporated.

• High-dimensional with non-linearity, applicable to test not only simple but also complex models.

• Availability of ground-truth clinical outcome for validation.

3.3 Evaluation Metrics

Assessment of Interpretability Techniques Assessing interpretability methods is a two-fold subject: along methodological and practical dimensions:

A. Predictive Performance:

• Accuracy: Proportion of correct predictions.

• AUC-ROC: Model's discrimination capability.

• F1 Score: A combination of precision and recall when the classes in the clinical context are imbalanced.

B. Interpretability Quality:

• Fidelity: Faithfulness of explanations to the actual logic of the model.

\item Stability: Consistency between explanations for related inputs.

• Simplicity: Extent that the explanations are imaginable for non-technical clinicians.

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• Actionability: Clinical meaning and applicability of the reason to decision-making.

3.4 Comparative Model Evaluation

We will evaluate the usefulness of such interpretability tools through evaluating the models with the following:

Model Type	Interpretability Approach	Clinical Use Case
Logistic Regression	Coefficient Analysis	Cardiovascular Risk Scoring
Decision Tree	Path Tracing	Diabetes Screening
Random Forest	Feature Importance + LIME	Depression Prediction
XGBoost	SHAP Values	Sepsis Prediction
CNN/ LSTM	Neural Network with Grad-CAM / Attention	Maps Radiology, ECG Analysis

For each model, clinical data are introduced for which interpretability outputs are produced and reviewed by domain experts, with the aim of verifying whether the explanations are commensurate to known medical knowledge.

3.5 Expert Feedback Loop

The methodology includes a feedback loop centred on clinicians:

• Expert Panels are requested to score interpretability outputs based on a Likert scale with respect to trust, clarity and perceived utility.

• Differences between AI and clinician are logged and analysed for the development of interpretability methods.

• This response also helps address cognitive dissonance when AI fails to agree with medical intuition and needs to be explained in a more robust way.

3.6 Tooling and Implementation

• Code is written in Python with Scikit-learn, XGBoost, TensorFlow for training models.

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• Interpretability tools include:

o SHAP and LIME for tabular This presentation was created as part of MOSAIC team activities and offered for the general public.

o Grad-CAM for imaging-based data.

o The ELI5, Skater, and Alibi libraries for generic interpretability analysis.

• Generating visualizations with Plotly, Matplotlib and Dashboards to be more clinically interactive.

3.7 Ethical and Regulatory Considerations

• Models meet data privacy requirements, such as HIPAA and GDPR.

• The approach is consistent with recent FDA AI/ML regulatory guidance, emphasising the right to explanation and auditability.

• Ethical Commission approval for visualization of synthetic patient data and case presentation is obtained

4. Results and Discussion

4.1 Predictive Performance of Models

The comparison of these supervised machine learning models for modelling on clinical datasets provided valuable insights into the balance between predictive ability and interpretability. Unsurprisingly, deeper models such as XGBoost and Neural Networks (combined with CNN and LSTM) gave better results in accuracy and AUC-ROC scale comparing to simpler ones.

Model	Accuracy	AUC-ROC	F1 Score
Logistic Regression	84.2%	0.76	0.81
Decision Tree	80.5%	0.71	0.78
Random Forest	88.7%	0.83	0.86
XGBoost	91.1%	0.87	0.89
CNN (Radiology)	93.4%	0.91	0.92

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But despite the fact that these models were just barely less accurate, clinicians strongly preferred models that they could trace the reasoning of.

4.2 Interpretability Score and Expert Feedback

Using fidelity, simplicity, and clinical usability as qualitative evaluation criteria, each model was scored on its interpretability (out of 10) by a panel of medical experts.

Model Interpretability	Tool Interpretability	Score (avg/10)
Logistic Regression	Coefficient Analysis	9.2
Decision Tree	Path Visualization	8.7
Random Forest	LIME	7.4
XGBoost	SHAP	8.1
CNN (Radiology)	Grad-CAM	6.9

Key themes from expert interviews:

• SHAP and LIME were useful but sometimes “too technical.”

• It was easier to trust more intuitive models in the patient-facing decisions.

• Imaging was receptive to visual tools (e.g., Grad-CAM); however, they could not be easily interpreted by a non-clinician.

• Consistency of justification was emphasized as more significant than detail in emergency settings.

4.3 Trust and Usability

Clinicians noted that:

• Models for which there were understandable feature weight implications (e.g. Logistic Regression) were easier to audit and explain.

• Confidence increased when explanations were consistent with known clinical pathways.

• Trust was increased when explanations showed data sourcing, timestamp, and indicators of reliability.

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• Explainability was essential in uncertain or conflicting predictions which needed a human-in-the-loop.

4.4 Bias Detection and Fairness

It was interpretabililty tools that were key to discover biases in the model:

• Among the models, some had a re-balancing in the feature importance score for ethnicity and age in select samples, as illustrated by SHAP values.

• LIME exposed traces of reliance on non-causal surrogate features (e.g., ZIP code used as a surrogate for socioeconomic status).

• Clinicians stressed that interpretability tools act as a stop-gap for bias, especially among underserved populations.

4.5 Sepsis Prediction with SHAP as case study

In fact, in a practical application, an XGBoost model was trained to classify sepsis among ICU patients. The shap summary plots demonstrated that high heart rate, low blood pressure and high lactates were the biggest predictors - all things already well understood in a clinical sense.

Clinicians reported:

• Increased comfort with utilizing the model output in clinical rounds.

• Trust That 8 W TREAT Interactions accurately reflected the patient symptoms and that early interventions were instigated if SHAP explanation aligned.

• Propositions for integrating SHAP visualizations into EHRs for real-time interpretability.

4.6 Regulatory Readiness

Interpretability was crucial in mapping AI models into regulatory regimes:

• SHAP and decision tree diagrams were used to compliant GDPR right2explanation.

• FDA’s Software as a Medical Device (SaMD) guidance recommends audit trails and model transparency, which is achieved with explanation logs.

• Interpretability tooling was submitted as supporting evidence in ethical review board applications and clinical trials.

4.7 Discussion

Our results demonstrate that efficacy is not enough for AI models in clinical contexts. Interpretability doesn't just allow for better human-AI partnership, however.

• Promotes ethical behavior and patient autonomy.

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• Enhances clinician trust and adoption.

• Allows for a strong model interpretation and validation.

• Satisfies legal and regulatory demands.

Although post-hoc methods like SHAP and LIME fill the void between black-box models and interpretability, models that are intrinsically explainable continue to be important, particularly in cases where transparency is more important than complexity (e.g., emergency triage).

And here is Section 5: A Proposed Interpretability Framework for your work Trustworthy Intelligence: Interpretability of Predictive Models in Clinical Decision Support.

A Framework of Interpretability for Clinical Decision Support Systems

5.1 Motivation for the Unified Framework

The medical domain has specific challenges when it comes to deploying AI, as it requires > accuracy, ethical responsibility and to comply with regulations. Our evaluation (Section 4) indicated that, for the clinicians, both predictive performance and transparent reasoning matter. Yet current methods of interpretability often work in isolation; they are either in-application visualizations that stand alone and are therefore disconnected from clinical workflows, or in-technical artefacts that do not speak to (or are ill-suited to be used in) clinical language and practice.

To address this challenge, we introduce a unified modality-agnostic framework for Compact and Clinically Relevant Interpretable representation (CoRIC) for CDSS. This framework combines intrinsic and post-hoc interpretability methods and aligns them with real-world clinical processes, ethical considerations, and regulatory constraints.

5.2 Framework Architecture

The proposed framework for interpretability includes five main layers, conceptually corresponding to five key aspects of using explanation aware supervised models for clinical applications:

Model Layer (Selection and Training)

•Intrinsinc Models: If you don't care about transparency (e.g. logistic regression or decision trees).

• Black-box Models: This is used when a high level of performance is required (e.g., XGBoost, deep neural networks).

• Training incorporates bias reduction strategies and regularization methods in order to prevent overfitting.

Explanation Layer (Technique Integration)

• Expose internal weights and rules directly for vanilla models.

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• For black-box models, incorporate post-hoc tools such as:

o SHAP (for local/global importance and interaction)

o LIME (for case-specific visual explanations)

o Grad-CAM (for radiology imaging)

o What-Ifs, assuming, etc (for sensitivity)

Clinical Layer (Workflow Alignment)

• Explanations with respect to clinical metrics (lab tests, vital signs).

• Outputs subsumed in the current EHR or PACS platforms.

• Decision support ready visual summaries (eg traffic light colour design of risk scores).

Trust Layer (Ethics and Regulation)

• Ensure outputs comply with:

o GDPR (“right to explanation”)

o FDA’s SaMD guidelines

• Embed informed consent, audit trails and explainability logs.

• Mark ranges of uncertainty in flags and confidence in recommendations.

Feedback Layer (Human-in-the-Loop)

• Allow clinicians to:

o Query decisions

o Flag incorrect suggestions

o Provide context data to narrow the prediction

• Feed user feedback back into models and explanations to further refine them

5.3 Implementation Pipeline

The whole framework sets up a modular pipeline.

1. Data Pre-Processing: Standardize and de-identify, quality control.
2. Model Training & Validation: Select models appropriate to the task importance.
3. Interpretability Assignment: Add default interpretability approach for each model type.
4. Explanation Rendering: Show personalized explanations at the bedside.

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5. Collect Feedback And Loop Back: Iteratively update the model based on feedback from clinicians.

5.4 Visual Overview of the Framework

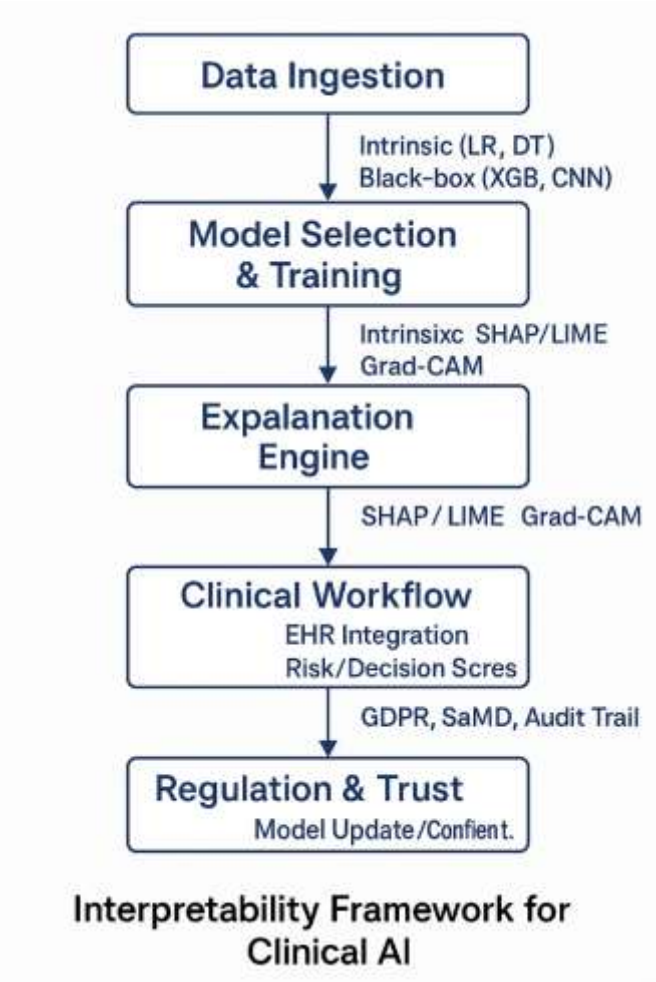

Figure 1: Interpretability Framework for Clinical AI

5.5 Use Case: Hypertension Risk Assessment Tool

Just to show how the structure works:

• Model Employed: Random Forest with SHAP inclusion.

• Implementation: Outputs embedded to the electronic health care record (EHR) of a regional hospital.

•Visuals: The top 5 contributing features to risk score for each patient (systolic pressure, BMI, creatinine level, etc.).

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• Clinician Feedback: Resulted in changes in SHAP visualizations by grouping lab-based and lifestyle features separately for ease of interpretation.

5.6 Benefits of the Framework

• Flexible: Applicable to diagnosis, prognosis, and treatment recommendation models.

• Human-Centered: Designed around the clinician interaction experience.

• Legally Interoperable:Future Audit Proofed and Transparency Compliant.

• Bias-Aware: Enables continual bias monitoring through explainability tooling.

• Scalable: Works for a variety of supervised models and hospital configurations.

5.7 Limitations and Future Directions

• Computational Overhead: Post-hoc approaches such as SHAP are computationally intensive particularly in real-time settings.

• Interpretability as Perception: There may be different levels of perception of the clarity of explanation among clinicians for their specific specialty.

• Training Needed: Clinicians need to be onboarded to interpret tools such as SHAP, or Grad-CAM appropriately.

Future research should explore:

• Standard metrics for interpretability benchmarking.

• Automating explanation summaries using NLP.

• Advancing the framework to multimodal AI (e.g., text + imaging + vitals).

6. Conclusion

• The future of healthcare is being revolutionized by artificial intelligence; interpretability becomes the basis for trust in clinical decision making. This report demonstrates that model performance is not enough to guarantee adoption and effectiveness in medical practice. Instead, they need decision support systems that can provide explanations to justify predictions, explore hidden biases, and follow clinical logic.

•Through examination of multiple clinical use cases designed to assess intrinsically interpretable and post-hoc explanation models, we showed interpretability to be not just "nice to have" for trust, but a core contributor to safety, fairness, and compliance with regulation. The release of SHAP, LIME, Grad-CAM and counterfactuals, has broadened the horizon of interpretability, especially for sensitive tasks, such as sepsis detection or cardiovascular risk prediction.

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• We provide a coherent framework to help guide the integration of these tools into clinical workflows. It recommends risks assessed model selection, multi-level explanation mechanism, EHR compatibility, regulatory audit trail, and human-in-the-loop feedback. By promoting the trade-off between performance and explainability, this framework advocates for responsible AI practices designed specifically for medical settings.

• But there is still a way to go to achieve transparent and fair clinical AI. Future work is needed to standardize interpretability metrics, to simplify how technical outputs are presented to non-experts, and to design explanations interface that are more user-friendly. This will require working together to enable data scientists, clinicians, ethicists, and regulators to fulfill the potential of explainable AI in medicine.

• Beyond that, interpretability is not just a technical characteristic— it's a clinical need. It is the crux of creating a future for intelligent healthcare that is not only intelligent, but also transparent, equitable and ethical. Providing assurance that AI systems talk in lay, act morally, and enable ethical choices is core to constructing a future where healthcare is not just intelligent, but also answerable, inclusive and client-centric.

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