International Journal of Medical Toxicology & Legal Medicine Volume 26, No. 3 and 4, 2023
e-ISSN: 0974-4614
p-ISSN: 0972-0448

Explainable Artificial Intelligence (XAI) Framework for Transparent Clinical Decision Support Systems

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Received: 18.09.2023 Revised: 07.10.2023 Accepted: 20.11.2023

ABSTRACT
Artificial Intelligence (AI), the branch of computer science concerned with building intelligent machines, is commencing its momentous entry into Clinical Decision Support (CDS) systems used during patient diagnosis and treatment. The lack of transparency and interpretability of the underlying mathematical models threatens the adoption of AI-enabled decision support tools in medicine. However, clinical safety hinges on user trust. Hence, transparency and interpretability constitute major tenets of Explainable AI (XAI), a field devoted to generating explanations in natural language, diagrams, or other forms suited to the anticipated end-user. Explanations delineate the relationship between the system input and output and support users in their clinical reasoning. To promote XAI in the context of a transparent clinical CDS framework, core principles are distilled from literature in XAI and CDS. Three high-level requirements emerge to guide specification engineering: the capability to present appropriate information to each actor at each decision milestone during the model lifecycle; the inclusion of mechanisms that enable users to ascertain that the explained outcome aligns with the expected outcome, if a similar situation were to arise; and the assurance of explanation usefulness in the context for which the AI approach was designed and deployed.

Keywords: Clinical Decision Support System, Explainable Artificial Intelligence, Interpretability, Transparency, Explainability, Clinical Decision Support (CDSS), Model Interpretability, Transparency in AI, Human-in-the-Loop Healthcare, Trustworthy AI, Feature Attribution, Rule-Based Reasoning, Model Validation and Verification, User-Centered Interface Design.

INTRODUCTION

Clinical Decision Support (CDS) systems harness data about previous patients to enhance clinical decisions for current cases. Core components of a CDS include input data, an inference model, a prediction or recommendation, and an explanation. Explanations should be user-friendly, delivered in natural language, and readily accessible on request. Although robust machine-learning methods often act as black boxes, clinicians require precise knowledge of why a system proposed a specific action. For instance, when a model suggests admitting a patient for heart failure, it is critical to grasp whether the recommendation is based on the patient's low blood pressure, high creatinine levels, age, or other factors. Providing explanations fosters transparency and interpretability, addressing both ethical and practical considerations of user trust. The Explainable Artificial Intelligence (XAI) Framework for Transparent Clinical Decision Support Systems enhances user trust through explanatory transparency. An XAI framework governs the development and validation of black-box machine.

Fig.1. Explainable Artificial Intelligence in Healthcare

Learning (ML) algorithms, mitigating risks arising from hid- den assumptions and biases. The framework recommends fea- tures, techniques, media, and granularity of explanations that suit the consumers of CDS services. Transparency may also facilitate the validation of predictions and recommendations by CDS SMEs and policy makers, covering households and communities.

A. Background and Significance

Clinical Decision Support (CDS) systems can enhance patient outcomes, but trusted, transparent, and interpretable models are essential for acceptance and effective use. XAI offers a path toward the development of trustworthy, transparent, and interpretable CDS systems and establishes criteria for actionable explanations suitable for both clinicians and patients. Explaining model predictions fosters clinical reasoning, builds patient-clinician trust when communicating risks, and aids shared decision-making in the complex modern medical environment. Still, the need for transparency, interpretability, and user trust in decision support extends well beyond XAI alone. Transparent, interpretable, and trustworthy systems must address the concerns of multiple stakeholders: patients, care providers, healthcare organizations, and regulators. Such systems respond to these concerns by offering understandable explanations and transparent clinical rationale, establishing the provenance of decisions and data, and providing interpretable risk models. Development of a truly XAI framework for CDS involves not only technical solutions but also responsible protocols for governance: the processes by which deep-learning models and their explanations are first validated and then continually monitored and audited throughout their lifecycle. The goal of transparency demands that these provable elements be auditable through secure digital trails. Moreover, human factors such as decision fatigue, boredom, and single-factor attention must also be dealt with, allowing for the focused, timely, minimum-mental-energy consumption of decision support. The approach taken is thus multi-layered, multi-stakeholder, and multidisciplinary, incorporating machine learning engineers, clinical experts, and digital-technology providers. While data quality, preparation, and label-bias issues are probably of greater importance for CDS than the explainability of the chosen prediction model, these remain crucial challenges since the ultimate goal is patient outcome.

BACKGROUND AND MOTIVATION

The term explainable artificial intelligence (XAI) encompasses a growing range of theories, techniques, and systems that can facilitate the understanding of and trusted decision-making by AI-based systems. The explanation of why an AI-based system is proposing a certain recommendation or decision is essential for the trust of the users or even for the overall operational system. Recent XAI literature has put forward many explanation techniques. A detailed comparison of explanation techniques is still to come, but in general, they can be classified as model-agnostic or model-specific. The explanations can target individual predictions or represent the behaviour of the model as a whole. These aspects are linked to the usefulness of the explanation, completeness, and fulfilment of the human reasoning goals. Explanations provide a better level of information for the user and have the potential to facilitate the clinical reasoning process, communicate risk, and share the decision-making process with the patient.

Clinical Decision Support Systems: Importance and Challenges

The integration of clinical decision support (CDS) systems usually occurs within a clinical setting where patient data becomes available after being acquired from the hospital information system (HIS) and laboratory information system (LIS). Alerts, warnings, or suggestions generated by the system need to be taken into consideration by the health professional within a clinical workflow. Usability studies indicate that such recommendations must be time-efficient and easy to read and comprehend in order for the professional

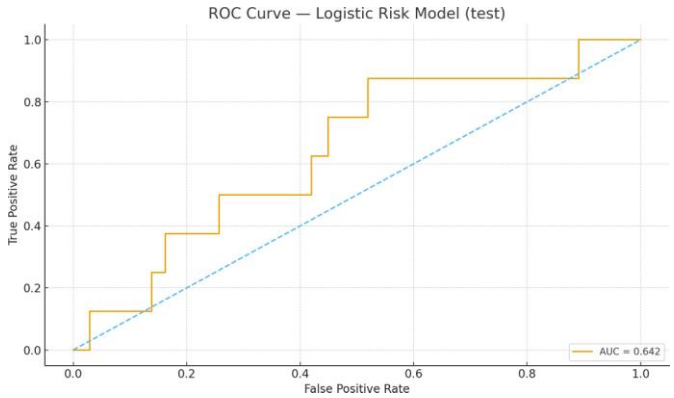

Fig.2. ROC Curve for Synthetic CDS Classifier

Table 1: Synthetic CDS Dataset Preview

age	sbp	creatinine	riskprob	outcome
81.9	117.5	1.357	0.0353	0
60.3	116.6	0.687	0.0113	0
65.3	117.2	1.1	0.0179	0
69.1	126.6	0.939	0.0147	0
57.1	120.9	0.843	0.0107	0
65	134.6	1.105	0.0126	0
65	113	0.771	0.0149	0
47.5	105.1	1.061	0.013	0
75.2	119.7	1.3	0.0266	0

support are imperative to successfully entering the clinical environment. The following data problems are relevant in order to integrate AI in the clinical decision-making process: data quality, bias, data interoperability, and compliance with legal-regulation authorities. XAI will help to promote and mitigation in these areas.

Equation 01: Logistic Risk Model (for illustration)

We use a simple clinical risk model

$$z_p=\beta_0+\beta_{\text{age}}\cdot\text{age}+\beta_{\text{sbp}}\cdot\text{sbp}+\beta_{\text{cre}}\cdot\text{creatinine},\ \sigma(z)=\frac{1}{1+e^{-z}}.$$

LIME fits a simple, interpretable model g near an instance x $g*\in\arg\ g\in G$ min local fidelity $L(f,g,\pi_x)+$ simplicity $\Omega(g)$

A common choice is a weighted ridge regression surrogate Let $X\in\mathrm{R}^{n\times d}$ be perturbed samples around x,$y=f(X)$ the black-box scores

Diagonal weights $W=$ diag $(\pi_x(X_i))$decay with distance from x

$\beta=(X^\top WX+\lambda I)^{-1}X^\top Wy$

Derivation: set gradient of $J(\beta)=(y-X\beta)^\top W(y-X\beta)+$

to act on the alert without taking too much attention from

$\lambda\|\beta\|^2$

to zero:$-2X^\top Wy+2X^\top WX\beta+2\lambda\beta=0\Rightarrow$

the other patient's information. Unfortunately, these alerts have been classified into three major categories that inhibit the decision-making process across all fields: data latency, alert fatigue, and data quality. Reasoning and explanation

$(X^\top WX+\lambda I)\beta=X^\top Wy$

This shows exactly how LIME's explanation weights arise from locality (W) and simplicity (λ).

A. Foundations of Explainable AI

Recent attention to explainable artificial intelligence (XAI) has been driven by incidents associated with autonomous vehicles and conversational agents that have occurred when users put high trust in their deployed systems. The importance of explanations in human reasoning, decision-making, and communication has long been recognized in psychology, cognition, detecting deception, and the legal system. People share and ask for explanations as part of natural interaction. Expectations for AI systems are no different. Indeed, explanations of decisions in sensitive domains such as law, finance, and health care are essential for managing trust and risk.

For clinical decision support systems (CDS), XAI is critical for safe integration. The high stakes of failure and operational context of CDS — an often latent AutoML methodology that relies on data flow from external systems; short response time within the critical path of clinical workflow; easing the cognitive load of busy or burned-out healthcare professionals (physicians, nurses) — demand XAI investment.

XAI addresses supervision in the AutoML closed-loop concept by providing explanations with the predicted probabilities and fostering confidence over the new observations available. It enables safety in the latent usage paradigm by clarifying risk. XAI assists with decision ownership, shared decision-making (SDM), and risk communication. After all, comparisons of diagnostic accuracy and models for predicting clinical outcomes or mortality in CDS do not consider the importance of explanations as necessary support for clinicians.

B. Clinical Decision Support Systems: Importance and Challenges

Clinical Decision Support Systems (CDS) are critical components of IT infrastructures within healthcare institutions, encompassing a range of applications that assist clinicians in making diagnostic, therapeutic, and prognostic decisions. These applications suggest actions based on patient conditions and combine patient data with medical knowledge. High-level clinical workflow maps delineate potential integration points for these systems.

However, CDS are most commonly employed in alert mode — the automation of reflex responses or the monitoring of abnormal condition transitions. Indeed, the concept of a smart hospital relies on timely alerts that facilitate the anticipation of clinical events, supporting preventive medicine and proactive real-time risk mitigation rather than reactive recovery.

Despite extensive efforts to enable the highest possible level of intelligent alerting, an almost parallel degree of frustration in biomedical safety management persists, attributed not only to data quality, bias, and interoperability challenges but also to alert fatigue. Alert fatigue arises from a critical group of emerging factors related to the ongoing and unsurpassed demand for cost savings in healthcare, which impact the development and maintenance of external validation cohorts for ML models. External validation is not typically attempted by the proposing researchers, despite ancillary recommendations provided in the first-generation AI literature. Properly addressing these factors would shorten the

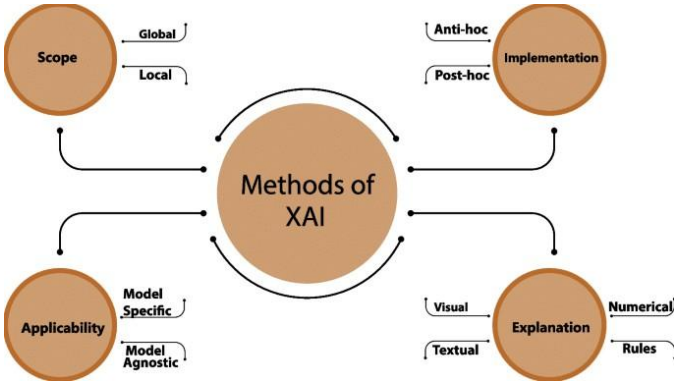

Fig.3. Core Principles of the XAI

gap between promising demonstration results and deployment in real-world scenarios. Within this context, the transparency, interpretability, and trust guarantees associated with Explain- able AI (XAI) represent a cornerstone to mitigate challenges, ensure user independence from the system, and ultimately sustain clinical decision-making processes in potentially life- threatening situations.

Core Principles of the XAI Framework

The Explainable Artificial Intelligence Framework for Transparent Clinical Decision Support Systems is built upon core principles that provide a transparent and interpretable architecture. Transparency is considered at the model layer, while interpretable machine learning methods and tools formulate the explanation layer. The notion of transparency encompasses the algorithmic and representational aspects of the system. Transparency at the algorithmic level considers the impact assessments and data quality requirements that the model design must satisfy, whereas the representational aspect analyses the form and granularity of explanations, taking various stakeholders into consideration. Interpretability in transparency indicates that the decision-making process is understandable by the intended recipient(s). Explanation accessibility and accountability are crucial for establishing trust in AI-assisted decision-making and automating the documentation of AI-assisted choices. They ensure that the questions who, when, and how the decisions made by the system can be answered at any time. The structured documentation of decision provenance facilitates justifying the automated actions taken or the actions advocated and permits attribution of knowledge, responsibility, and liability in the event of an incident. Supervised validation and retrospective examination of the decisions of transparent clinical decision support systems serve to assess and verify the benefit concordance and enhance the clinical governance of the model. XAI serves as a meta-regulator for clinical decision support systems.

A. Transparency and Interpretability

To gain trust in these technologies, transparency and interpretability become pivotal and imply the possibility to understand a model in terms of human concepts or to understand the reason a system produces a certain output for a certain input. Transparency can be seen at different levels: a model is transparent if the human can understand either how the model works overall or how it produces a certain response for a given input. The higher the transparency of a model, the lesser the need for humanly interpretable explanations. Different types of users expect different types of explanations. In the healthcare domain, different types of users are involved in the decision process. Clinical decision support systems should provide the information in the forms that are better understandable for the different users in the process, at the right granularity and level of detail. For clinical explanations, the aim of producing some triggering factors or suggestions that can support or complement the human reasoning process is important. To convey the information to patients that are not medical experts, one approach is to use visual representations that can better explain the information. In the case of narrative

explanations, the focus is on producing narrative reports that present the information with human-understandable words and structure.

B. Accountability and Governance

Roles, decisions, and the provenance of risk-based AI predictions must be clear and consistent across all stakeholders to provide clinicians, patients, and healthcare-encompassing decision-making ecosystems with the trust needed to support risk management, governance, and adherence to obligations and preferences. The likely outcomes of an AI prediction must be clearly auditable across the five phases of an Outcome Assurance Framework. Audit trails must specify the current version of every underlying model (the machine learning models and auxiliary models supporting the model-agnostic case-based reasoning) and support decisions on whether the latest model should be configured for production. The validity and safety of the explanation mechanism that has been deployed into production must be recorded in a monitoring history. The governance processes and controls of every model must ensure that suitable new data are being monitored, retained, and preprocessed while decisions post data collection should trigger a version update on the governing explanation model for the CDS used in the production system. Whenever a model update is likely to affect the quality of the explanation mechanisms supporting an AI product, those explanations must be checked and revised with an incident-response procedure that includes checking the suitability of explanations for use in

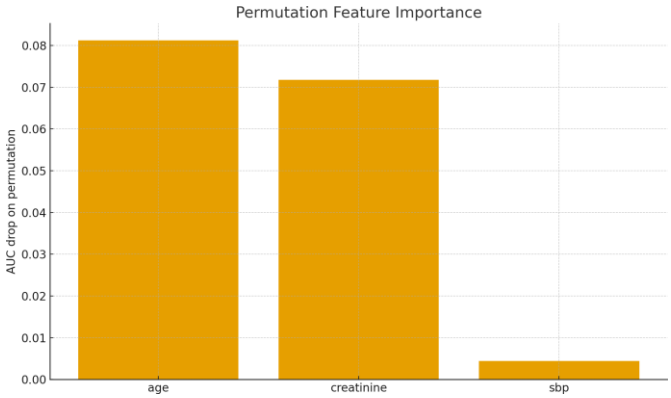

Fig.4. Permutation Feature Importance (higher=more important)

Table 2: Local Attributions (Shapley-style) for One Patient

	feature	value	contribution	
0	age	81.9	0.012209	
2	creatinine	1.357	0.006658	
1	sbp	117.5	0.0005	

How the explanation data is expressed, the level of detail, whether it is delivered for all requests or only those flagged by the internal monitoring and control service, and how it is synchronized with the latest CDSS output or model prediction. A transparent neural model will thus support explanations through other model-agnostic techniques in parallel with the implementation of the first basic component of explainability support. Four layers are involved: the data layer, the model layer, the explanation layer, and the user-interface layer. The layer-focused representation further indicates the various source components and logical interconnections. The top layer provides explanation services to the end users and, where applicable, forwards monitoring requests to the explanation layer. Both explanation types rely on the same data path but produce very different outputs: the model-agnostic methods for expressing the explanation typically used by clinicians and patients, such as a tabular format for SHAP, and the model-specific version necessary for reflecting the internal behavior or matches of the transparent neural model itself.

Equation 02: SHAP(Shapley values)—definition & constructive computation

shared decision-making with patients and for communicating risk with stakeholders such as parents and guardians.

Architectural Overview

$$\varphi_j = \sum_{S \subseteq F \setminus \{j\}} \frac{|S|!(M-|S|-1)!}{M!}$$

$(v(S\cup\{j\})-v(S))$.
$M!$ (1)

The rationale for a layered architectural design is twofold. First, like neural networks, explanation provision can be considered a separate sub function that operates over the model outputs, and consequently, the explanation interface can be conceptually separated from the model. Second, while an interface controls access to the explanation services, it also finalizes the user-facing explanation by determining

A. Layered Framework Design

The Explainable Artificial Intelligence Framework for Transparent Clinical Decision Support Systems (XAI Framework) is a layered structure comprising Model, Explanation, User Interface, Data Provenance and Quality, and Evaluation layers. The Model Layer encompasses the CDSML and candidate-bias models and is the most critical layer in clinical XAI systems. Explanations are generated using techniques described in the Methodology section and delivered via the User Interface Layer, while the Data Provenance and Quality Layer prepares input data for the Model Layer, covering sourcing, transformations, and quality measures. Each layer exposes an interface for data flow into and out of the layer, facilitating a systematic start-to-finish XAI-enabled CDSML. Generated explanations travel backward through the layered architecture and up to end users. Inputs from the Data Provenance and Quality Layer travel through to the Model Layer for the creation of the candidate-bias model and input data hygiene checks and quality-assurance tasks.

B. Data Provenance and Quality Assurance

Data provenance supports the monitoring of data quality and the mitigation of emerging biases. It comprises detailed documentation of data lineage, sourcing of external datasets, preprocessing with domain knowledge and quality metrics, data hygiene checks, and governance controls. For a given data source, all relevant details — including ethnic or geographic characteristics, age, and gender distributions — are explicitly cataloged. These attributes should also be monitored when downstream tasks rely on the integrity of those data.

For critical sources, periodic updates with replication studies would be preferable; for others, irregular checks may suffice. External datasets are subjected to a strong auditing process during the initial implementation stage. Subsequent use requires explicit user consent, under predefined conditions. Beyond checking for processing errors or slight label shifts, an auxiliary system verifies compatibility with prevailing clinical guidelines or literature. When quality falls below a certain threshold, use is automatically disallowed until the provider rectifies the issue.

For general CDS and external aids, strict controls ensure that changes in ethnic or geographic representation, age distribution, and other pertinent shifts trigger user alerts before action or use is attempted.

Methodological Components

The explainability of machine learning models is often achieved through the use of model-agnostic techniques. Such techniques do not require any knowledge of the model architecture, parameters, or features. A few of them designed for XAI in clinical settings include (i) feature-level importance assigned to various covariates using permuted Shapley values (SHAP), (ii) local surrogate models that are interpretable in hospitalization terms (LIME), and (iii) counterfactual explanations based on vector-based representations of patients that encode differences between the actual patient and those of the nearest neighbors in patient-feature space.

Recent integration of case-based reasoning in the attribution space of machine learning has demonstrated that machine learning models can also explain their decisions using explanation cases. The case-based reasoning mechanism, with an inbuilt feature selection methodology, allows the system to navigate through the entire explanation space of any classification problem and select information- and knowledge-rich cases for clinically interpretable explanations.

Similarity metrics also contribute significantly to the quality of explanations. Consequently, expert domain knowledge in CDS systems needs to be encoded in the definition of the similarity metrics to articulate “why a model made certain predictions.” Although some explanation techniques, such as counterfactual explanations, provide important insights when analyzing structural stability and local behavior, theirs is often a difficult line of reasoning for more complex models. Hence, it becomes necessary to augment their use with another line of reasoning that does not analyze the “how” of the model but focuses on “why” a model made certain predictions. Integrating causal inference into the explanation layer can facilitate the generation of actionable explanations and counterfactuals, hence ensuring that the explanations are not merely post hoc but also functional for clinicians.

A. Model-Agnostic Explanation Techniques

Several widely used model-agnostic explanation techniques support various interpretability tasks, but their explanations must specifically align with clinicians’ mental models for successful usage. Feature importance

methods (e.g., permutation importance, mean decrease impurity) generally satisfy this requirement and quantify the importance of variables for model predictions.

Conversely, SHAP and LIME decompose a single prediction into contributions from all features to the final output. While SHAP strives for consistent approximations across the input space using additive feature attribution, LIME selects interpretable local surrogate models for each prediction and has been effectively used for image and text classification.

Other methods draw analogies to human reasoning, such as counterfactuals, whereby the conditions under which the prediction changes are identified. Despite being model-agnostic, counterfactuals can be **directive** (when the chosen direction indicates an action, e.g., *"give aspirin to prevent a second heart attack"*) or **evaluative** (e.g., *"why did I survive an accident?"*). They have also been used in conjunction with causal inference to confirm patient survival during a process of elimination.

The chosen technique for a given model prediction should ultimately match the type of interpretative task being performed, remaining attentive to the method's scope and limitations. Although these methods are model-agnostic, they do not apply generically to every model. For instance, SHAP can operate only on models capable of input perturbation inference, and LIME (particularly LIME-LimeM) can only use discrete predictors and cannot tolerate class imbalances.

Furthermore, in instances where the model fails to generalize well, these techniques could yield misleading explanations; thus, results must be interpreted cautiously. Notable future developments that could enhance the model-agnostic capabilities of SHAP and LIME include the creation of new similarity measures and distances around prediction neighborhoods, support for probabilistic predictions, and the ability to provide explanations for sub-populations.

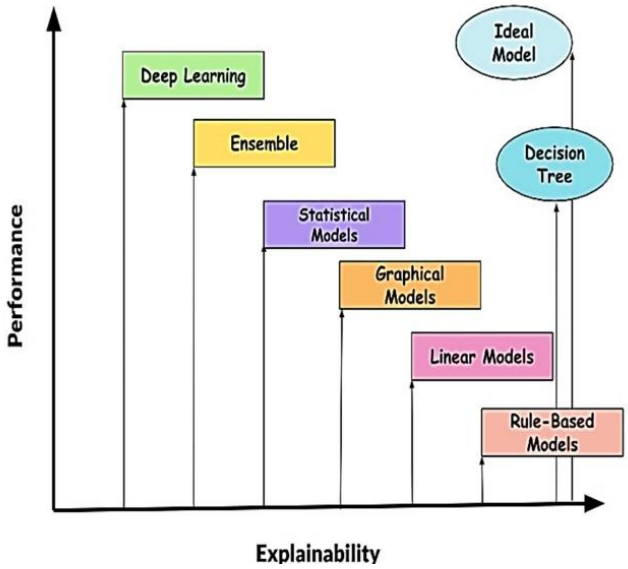

Fig.5. Model-agnostic explain able artificial intelligence

B. Case-Based Reasoning and Causal Inference

Case-based reasoning (CBR) is a problem-solving paradigm that leverages an archive of previous experiences to derive solutions for novel situations. In CBR, a new problem is solved by retrieving a similar past case, reusing the solution, and learning from the failure and success of this reuse. Explanations generated through CBR provide a reason for the decision by grounding it in prior occurrences with similar contexts, thus elucidating the underlying rationale.

Supporting the clinical requirement for decision justification, the critical question addressed by CBR within CDS is "Why?" A survey of explanation methods for pattern-classification systems reports a range of CBR methods that provide attribution of the model's decision in a form similar to the original training decision. Central to a CBR-based explanation is the choice of similarity metric. Selection of an appropriate metric translates the aspects that are most relevant for explaining the classification.

Counterfactual reasoning augments CBR by supplying a "What if?" interrogative, permitting the exploration of alternative scenarios through changes to influential variables. Causal inference methods go beyond correlations to reason about interventions—that is, the likely outcomes that would follow if the variables of the model were changed. These methods help answer the question "What are my options?" by producing "do" statements. CDS equipped with causal-explanation capabilities can generate recommendations that take into account likely outcomes of intervention.

Causal frameworks provide insight into how different variables affect others. Causal-explanation frameworks for time-sequenced data with input signal-shape variables can yield templates for interpretable surgeons' recommendations with specific criticism grounds.

Table 3: Top-5 similar cases(CBR-style)

	age	sbp	creatinine	riskprob
88	80.3	118.5	1.392	0.034
162	83.6	107.5	1.383	0.0458
154	75.9	122.1	1.38	0.0277
8	75.2	119.7	1.3	0.0266
219	70.9	116.4	1.35	0.0261

CONCLUSION

Trends in XAI that are relevant for clinical decision support systems and other areas with a human-in-the-loop character include scaling XAI methods to large models and datasets via model-specific, lower-fidelity approaches; refining explanations so they are more useful for the end user, possibly through advice from information scientists; and exploring new classes of explanations, such as debugging aids and counterfactuals.

New methods often lack robust validation in real-world applications. Concurrently, clinical validation of explainable estimations and predictions, ideally involving clinicians, is becoming a necessity. Regulatory agencies have many ongoing discussions about AI and machine learning and how to approach certification. The shift toward independence and third-party provisioning of data and pipelines may change the AI deployment landscape, create new data formats and applications that require little extra effort from clinical users, and shift the ownership of large-scale state implications and expenses into the research field.

In this context, an external performance and safety review comparable to the performance referred to above will be needed. However, these developments will take time and require an enormous amount of resources. Scalability, real-world validation, and regulation evolution are topics that will emerge naturally.

The most pressing points concern the actual deployment and use of XAI in clinical decision support. XAI is only one of many possible mitigation measures. The final approach—whether multilayered, hierarchical, or a different arrangement—will depend on the target candidates in terms of representativeness and effort needed. Big data, big surveys, patient involvement, and the strength of evidence have their own courses. In the meantime, the mechanism and provision of explanations can be treated separately for different models, ranging from black-box to case-based ground-truth systems. Failure to address these topics would compromise the evolution of a reliable AI-supported healthcare delivery system.

Equation 03: Permutation feature importance — AUROC-drop definition

$$Imp(j)=E[AUC(f(X))-AUC(f(X(j)))]. \quad (2)$$

A. Future Trends

Recent years have witnessed increased research interest in Explainable Artificial Intelligence (XAI) for Clinical Decision Support Systems (CDS). However, many early exploratory

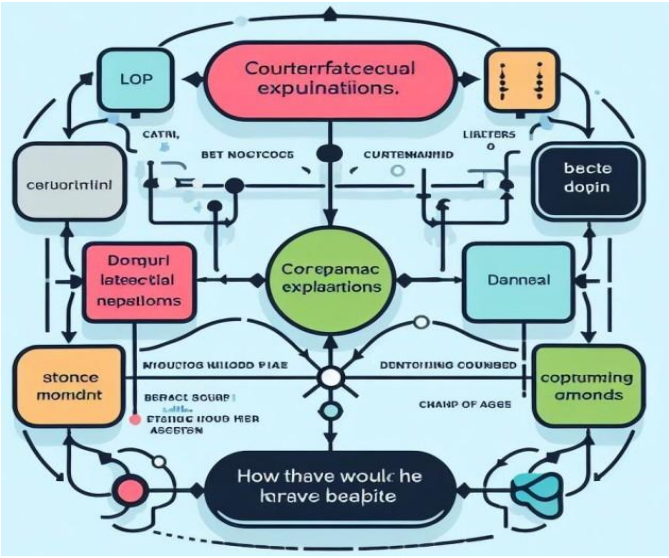

Fig.6. Counter factual Risk Reduction (patient 0)

studies have proposed local, isolated, and nonsystematic im- plementation of XAI techniques while failing to consider the broader interaction paradigm for different levels of clinical users or the resulting governance and accountability implica- tions. Moving forward, a comprehensive systematic roadmap should emerge, addressing these shortcomings, and enablinga scalable ecosystem that instills trust among patients and clinicians for real-world deployment of complex machine- learning-based classifiers. These advances are expected to en- able scalable implementation methodologies for layered CDS architecture, capable of integrating XAI support at different granularity levels for various clinical stakeholders. More-over, the availability of large annotated real-world datasetsfor training will facilitate the application of model-specific explanation techniques, particularly for deep-learning classi- fiers, and support validation of model-agnostic approaches. Simultaneously, regulatory bodies are likely to impose stricter auditing and monitoring requirements on predictive machine- learning classifiers, accelerating the growth of a genuine XAI ecosystem capable of delivering actionable explanations that support clinical reasoning, risk communication, and shared decision-making with patients.

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