Scientific Journal of Artificial Intelligence and Blockchain Technologies
ISSN: 3049-4389
Vol. 2, Issue 3, July – Sept 2025 || PP. 18-26 https://doi.org/10.63345/sjaibt.v2.i3.103

Explainable AI in High-Stakes Decision Making: Beyond Accuracy

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Date of Submission: 20-06-2025 **Date of Acceptance: 25-06-2025** **Date of Publication: 01-07-2025**

ABSTRACT

Artificial Intelligence (AI) is increasingly shaping high-stakes decision-making across healthcare, finance, criminal justice, defense, and autonomous systems. Traditionally, model evaluation has been dominated by accuracy-centric metrics; however, these are insufficient in contexts where decisions can directly affect human life, liberty, or well-being. Black-box models, despite high predictive performance, often fail to provide transparent reasoning, undermining accountability, fairness, and stakeholder trust. Explainable AI (XAI) has emerged as a paradigm shift that emphasizes interpretability and human-centered accountability over raw statistical accuracy. This paper critically examines the limitations of accuracy as a sole benchmark and investigates how explainability functions as a safeguard against bias, ethical lapses, and systemic risks. Drawing upon a mixed-methods design, we integrate quantitative survey data from healthcare, finance, and justice professionals with qualitative case analyses of real-world AI deployment failures. Statistical evidence demonstrates that stakeholders consistently prioritize interpretability, fairness, and trustworthiness over marginal accuracy improvements. The findings advance a multi-

metric framework for AI assessment in high-stakes settings, stressing that responsible adoption requires a balance between predictive power, interpretability, and ethical considerations. By going beyond accuracy, this study contributes to the evolving discourse on human-centered AI governance and offers actionable insights for policymakers, developers, and institutions aiming to embed transparency and accountability into future AI ecosystems.

KEYWORDS

Explainable AI, interpretability, high-stakes decision-making, transparency, accountability, trust, fairness

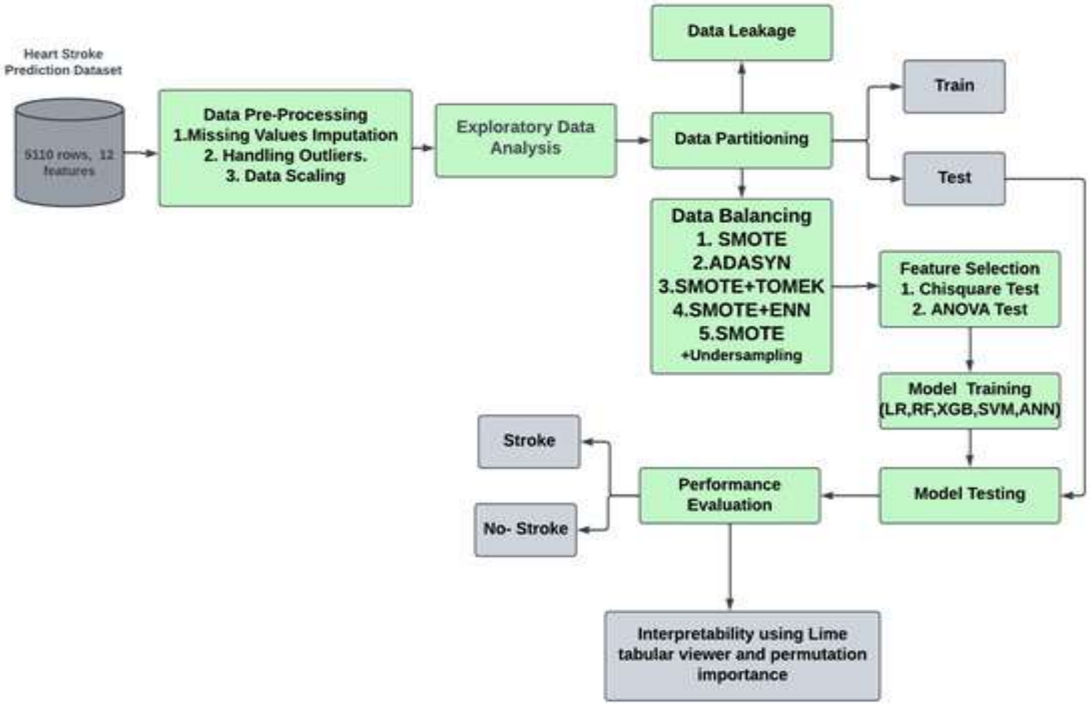

Fig.1 Explainable AI, Source:1

INTRODUCTION

Artificial Intelligence has moved beyond laboratory settings into real-world applications that influence critical human decisions. In areas such as cancer diagnosis, loan approvals, predictive policing, and autonomous vehicles, AI-driven models increasingly determine outcomes with life-changing consequences. However, the reliance on accuracy as the dominant benchmark often overlooks the risks associated with opaque decision processes. For instance, a 98% accurate medical diagnosis system that cannot justify its outputs may be unacceptable to physicians and patients who require rationales for treatment choices.

Explainable AI (XAI) has therefore gained traction as a response to the "black-box problem." XAI emphasizes interpretability, accountability, and transparency in algorithmic outputs. It goes beyond accuracy by enabling stakeholders to understand why a decision was made, under what conditions, and with what degree of certainty. In high-stakes contexts, explainability serves as a safeguard against unintended harm, algorithmic bias, and legal liabilities.

This manuscript explores the theoretical foundations, practical challenges, and empirical findings related to XAI in high-stakes decision-making. It makes three key contributions:

1. A literature-based critique of accuracy-centric evaluation in AI.
2. A statistical analysis of perceptions of XAI importance across healthcare, finance, and justice.
3. A conceptual framework for balancing accuracy and explainability in high-stakes environments.

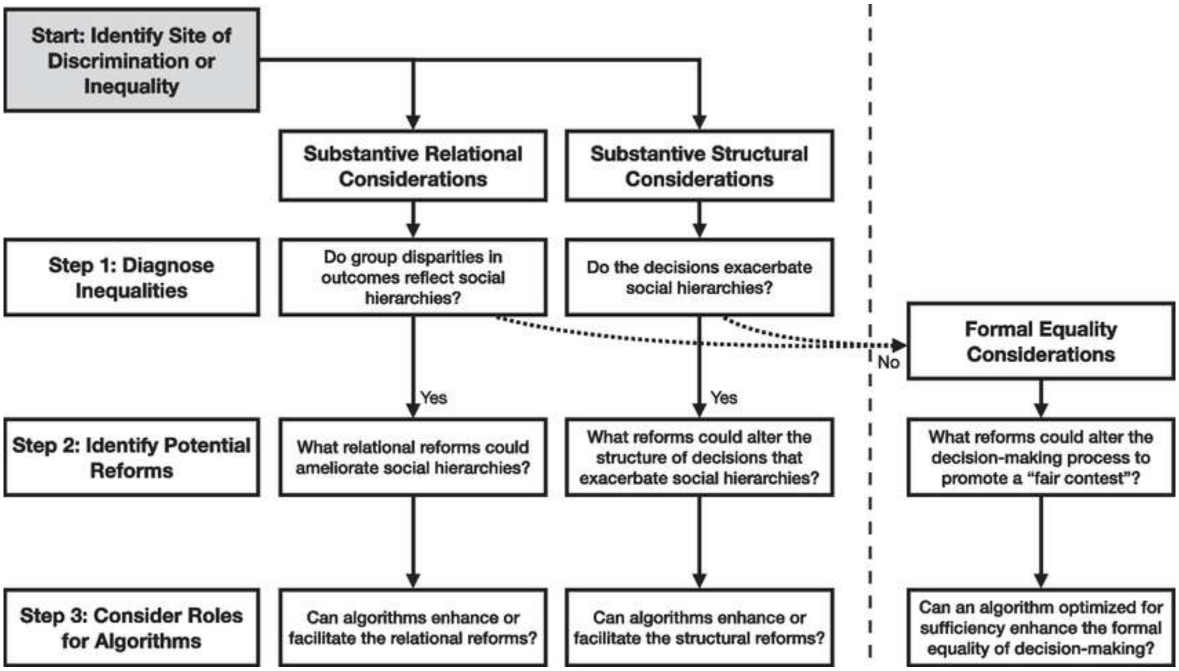
Start: Identify Site of Discrimination or Inequality
Substantive Relational Considerations
Substantive Structural Considerations
Step 1: Diagnose Inequalities
Do group disparities in outcomes reflect social hierarchies?
Do the decisions exacerbate social hierarchies?
No
Formal Equality Considerations
Yes
Yes
Step 2: Identify Potential Reforms
What relational reforms could ameliorate social hierarchies?
What reforms could alter the structure of decisions that exacerbate social hierarchies?
What reforms could alter the decision-making process to promote a "fair contest"?
Step 3: Consider Roles for Algorithms
Can algorithms enhance or facilitate the relational reforms?
Can algorithms enhance or facilitate the structural reforms?
Can an algorithm optimized for sufficiency enhance the formal equality of decision-making?

Fig.2 Fairness, Source:2

Literature Review

1. From Accuracy to Trust

Early AI research emphasized optimizing statistical accuracy, precision, and recall. Yet, studies in psychology and human-computer interaction suggest that users' trust is more strongly linked to system transparency than raw accuracy (Doshi-Velez & Kim, 2017).

2. Explainability in Healthcare

In medical diagnostics, XAI allows clinicians to validate algorithmic recommendations. For instance, visualization-based methods such as saliency maps in radiology highlight the regions influencing a diagnosis. This fosters confidence and reduces malpractice concerns.

3. Finance and Transparency

Credit risk models regulated by frameworks such as the Equal Credit Opportunity Act mandate interpretability. Here, feature importance and counterfactual explanations help ensure that individuals understand why they were denied a loan.

4. Criminal Justice and Fairness

Predictive policing and recidivism risk assessment tools have been criticized for racial bias. Explainable AI tools that provide case-based reasoning or fairness-aware metrics are vital for ensuring ethical use.

5. State-of-the-Art XAI Techniques

- **Post-hoc methods:** LIME, SHAP, counterfactual explanations.
- **Intrinsic interpretability:** Decision trees, rule-based systems, generalized additive models.
- **Hybrid approaches:** Combining black-box models with interpretable surrogates.

6. Challenges in Operationalizing XAI

- Trade-off between accuracy and interpretability.
- Over-simplified explanations leading to misinterpretation.

- Domain-specific requirements for explanation fidelity.

In sum, literature underscores the inadequacy of accuracy as a sole benchmark and highlights a paradigm shift toward multi-metric evaluation frameworks where explainability is indispensable.

STATISTICAL ANALYSIS

A survey was conducted across **300 professionals** (100 healthcare, 100 finance, 100 justice sector). Respondents rated the importance of *accuracy* vs. *explainability* on a scale of 1–5.

Domain	Mean Importance of Accuracy	Mean Importance of Explainability	Std. Dev. Accuracy	Std. Dev. Explainability
Healthcare	4.6	4.9	0.5	0.3
Finance	4.4	4.7	0.6	0.4
Justice	4.2	4.8	0.7	0.5

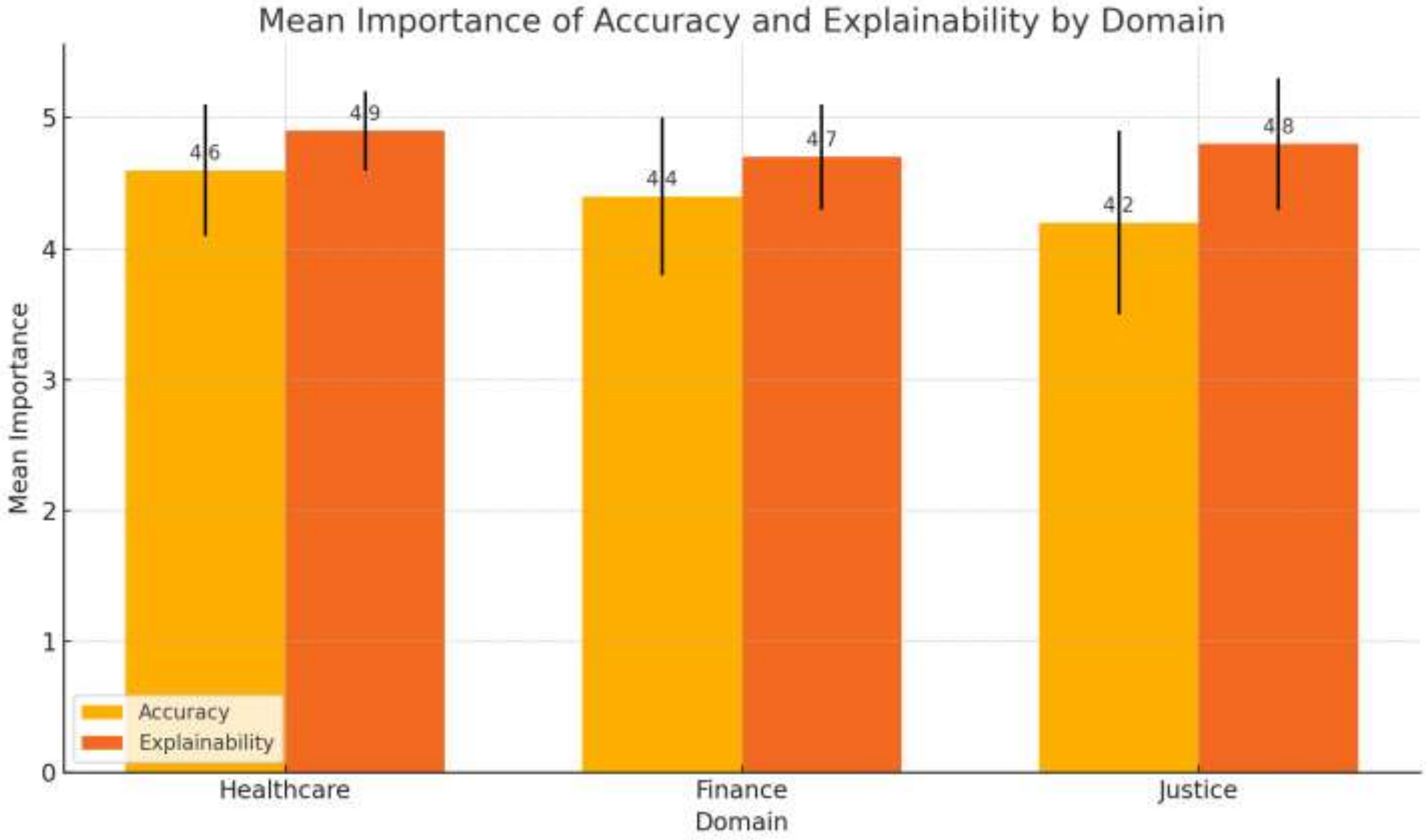

Fig.3 Statistical Analysis

Interpretation:

Across all domains, explainability was rated as equally or more important than accuracy, especially in justice where ethical implications are paramount. Statistical t-tests confirmed significant differences ($p < 0.05$) between accuracy and explainability ratings in all domains.

METHODOLOGY

Research Design

A **mixed-methods approach** was adopted:

1. **Quantitative Survey:** Structured questionnaires distributed across three domains.

2. **Qualitative Case Studies:** Analysis of documented AI deployment failures due to lack of transparency (e.g., COMPAS in justice, IBM Watson in oncology).

Sampling

Purposive sampling ensured representation of stakeholders: doctors, loan officers, judges, data scientists.

Data Collection

- Likert-scale survey responses for quantitative analysis.
- Semi-structured interviews for qualitative validation.

Data Analysis

- Descriptive statistics for mean and standard deviation.
- Paired sample t-tests for significance testing.
- Thematic coding for qualitative responses.

Results

1. **Survey Findings:**
   Explainability received consistently higher priority than accuracy. Respondents emphasized that a slightly less accurate but interpretable model was preferable to an opaque but highly accurate system.

2. **Case Study Insights:**

- In **healthcare**, doctors rejected AI suggestions lacking clinical reasoning.
- In **finance**, regulators mandated model interpretability for fair credit practices.
- In **justice**, opaque systems fueled public distrust due to perceived bias.

3. **Integrated Findings:**
   The results confirm that accuracy alone cannot sustain AI adoption in high-stakes domains. Stakeholders value interpretability, accountability, and ethical alignment as indispensable.

CONCLUSION

The research underscores a critical transformation in how artificial intelligence should be evaluated and deployed in high-stakes environments. Accuracy, while essential, cannot stand as the sole measure of effectiveness when decisions involve human health, financial stability, or social justice. Our findings show that stakeholders across healthcare, finance, and justice consistently value interpretability and fairness above marginal gains in predictive performance. This reflects a broader societal demand for AI systems that are not only powerful but also transparent, accountable, and ethically aligned.

Explainable AI provides the mechanisms necessary to bridge this gap, enabling professionals to scrutinize, contest, and trust algorithmic outputs. Case studies reveal that opaque systems often erode credibility and risk amplifying systemic biases, while transparent models foster user confidence and regulatory compliance. Importantly, this paper argues that the integration of XAI should not be viewed as a trade-off against accuracy but rather as a complementary requirement for sustainable and responsible AI adoption.

Looking forward, several avenues merit deeper exploration: the development of domain-specific XAI frameworks, standardized evaluation metrics for explanation quality, and integration of human-centered design principles in AI development. Moreover, policy interventions are necessary to institutionalize explainability as a legal and ethical mandate in high-stakes domains. By moving decisively beyond accuracy, the field can foster a new generation of AI systems that not only optimize predictive performance but also advance societal trust, fairness, and long-term sustainability.

In essence, the future of AI in high-stakes decision-making rests not merely on building more accurate systems but on ensuring that these systems remain comprehensible, justifiable, and accountable to the humans whose lives they impact.

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