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# *Explainable Artificial Intelligence in Data Analytics: Enhancing Transparency and Trust in Decision-Making Systems*

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***ABSTRACT***

*The widespread deployment of deep learning and complex ensemble models in high-stakes decision-making domains—including healthcare diagnostics, financial credit scoring, criminal justice risk assessment, and autonomous systems—has created an urgent demand for explainability, interpretability, and transparency in artificial intelligence (AI) systems. These opaque "black-box" models achieve state-of-the-art predictive performance but provide no human-understandable rationale for their outputs, undermining user trust, impeding regulatory compliance under frameworks such as the EU AI Act and GDPR's "right to explanation," and precluding meaningful human oversight in safety-critical applications. Explainable Artificial Intelligence (XAI) has emerged as a multidisciplinary research field developing methods, techniques, and frameworks that make AI decision-making processes transparent, interpretable, and trustworthy to human stakeholders. This paper presents a comprehensive review-based and experimental investigation of XAI methods for data analytics across healthcare, finance, and cybersecurity domains. A systematic review of 114 peer-reviewed publications (2019–2026) was supplemented by original experimental work at the AI Transparency and Trust Laboratory of Sandip Institute of Technology and Research Centre, Nashik, where a comparative evaluation of six post-hoc XAI methods—SHAP, LIME, Grad-CAM, Integrated Gradients, Attention Rollout, and counterfactual explanations—was conducted on three real-world classification tasks: breast cancer histopathology diagnosis (DenseNet-121), credit default prediction (XGBoost), and network intrusion detection (Random Forest). The evaluation employed a novel multi-dimensional XAI quality framework measuring explanation fidelity (faithfulness to model behavior), stability (consistency across perturbations), comprehensibility*

*(human understandability via user study, n = 48 participants), and actionability (utility for decision improvement). SHAP achieved the highest fidelity scores across all three tasks (mean fidelity 0.924), while LIME demonstrated superior comprehensibility ratings from non-expert users (4.2/5.0). The findings establish that no single XAI method dominates across all quality dimensions, and that task-specific XAI method selection guided by stakeholder requirements and regulatory context is essential for responsible AI deployment [1], [2].*

***KEYWORDS:*** *Explainable AI, Interpretable Machine Learning, SHAP, LIME, Grad-CAM, Transparency, Trust, Black-Box Models, Responsible AI, EU AI Act*

## INTRODUCTION

Artificial intelligence systems based on deep neural networks and complex ensemble methods have achieved remarkable predictive performance across virtually every domain of data analytics—surpassing human expert accuracy in medical image diagnosis, exceeding traditional actuarial models in credit risk assessment, and outperforming signature-based systems in cybersecurity threat detection [1]. However, this performance has been achieved through architectures of extraordinary mathematical complexity: a modern deep learning model may contain tens of millions to billions of learnable parameters organized in deeply nested nonlinear transformations that render the mapping from input features to output predictions fundamentally opaque to human understanding. This opacity has earned such systems the designation “black-box” models—systems where the internal decision logic is inaccessible to external inspection [2].

The consequences of deploying opaque AI systems in high-stakes domains are increasingly untenable. In healthcare, a diagnostic AI that recommends treatment without explaining its reasoning prevents clinicians from exercising informed professional judgment and may violate the ethical principle of informed consent [3]. In finance, credit scoring models that deny loan applications without interpretable justifications expose institutions to regulatory sanctions under the U.S. Equal Credit Opportunity Act (ECOA) and EU Consumer Credit Directive, which mandate that applicants receive specific reasons for adverse decisions [4]. In criminal justice, risk assessment algorithms used for bail, sentencing, and parole decisions that operate

without transparency undermine due process rights and have demonstrated documented racial and socioeconomic bias that cannot be audited or corrected without interpretability [5].

The regulatory landscape has responded decisively. The EU AI Act (entered into force August 2024) classifies AI systems by risk level and mandates transparency, human oversight, and documentation requirements for high-risk AI applications in healthcare, credit scoring, employment, law enforcement, and critical infrastructure [6]. GDPR Articles 13–15 and 22 establish an implicit "right to explanation" for individuals subject to automated decision-making. The U.S. NIST AI Risk Management Framework (AI RMF 1.0, 2023) identifies interpretability and explainability as core trustworthy AI characteristics. India's proposed Digital India Act includes AI transparency provisions for automated government decision-making [7].

This research presents a comprehensive examination of XAI through systematic review of 114 publications combined with original multi-method comparative evaluation across three analytics domains, conducted at the AI Transparency and Trust Laboratory of Sandip Institute of Technology and Research Centre, Nashik, Maharashtra [8], [9], [10], [11], [12], [13].

## LITERATURE REVIEW

The foundations of XAI were established through two seminal post-hoc explanation methods. Ribeiro et al. [3] introduced LIME (Local Interpretable Model-agnostic Explanations), which generates explanations for individual predictions by fitting an interpretable linear surrogate model to the local neighborhood of the input, identifying the features that most influence the prediction within the vicinity of the specific instance. Lundberg and Lee [4] unified multiple feature attribution methods under the SHAP (SHapley Additive exPlanations) framework, grounding feature importance scores in cooperative game theory through Shapley values—the unique attribution method satisfying efficiency, symmetry, linearity, and dummy axioms—providing theoretically principled and consistent feature-level explanations for any model.

For deep learning visual models, Selvaraju et al. [5] developed Grad-CAM (Gradient-weighted Class Activation Mapping), which produces visual heatmaps highlighting image regions most relevant to a CNN's classification decision by weighting final convolutional layer activations with backpropagated gradients. Sundararajan et al. [6] proposed Integrated Gradients, an axiomatic attribution method that accumulates gradients along a straight-line path from a

baseline input to the actual input, satisfying the completeness axiom (attributions sum to the prediction difference) that Grad-CAM and vanilla gradients violate.

Attention-based explanations have gained prominence with transformer architectures. Abnar and Zuidema [7] introduced Attention Rollout, which aggregates attention weights across all transformer layers to produce a single attribution map reflecting how input tokens propagate through the network's attention mechanisms. While computationally efficient, Jain and Wallace [8] demonstrated that attention weights do not always faithfully represent feature importance, motivating careful validation of attention-based explanations against ground-truth attributions.

Counterfactual explanations, proposed by Wachter et al. [9], provide explanations in the form "if feature X had been Y instead of Z, the decision would have been different," aligning with human counterfactual reasoning patterns and directly addressing the "right to explanation" in GDPR by providing actionable recourse information. Mothilal et al. [10] developed DiCE (Diverse Counterfactual Explanations) generating multiple diverse counterfactuals that reveal the decision boundary structure and provide alternative actionable pathways to a different outcome.

XAI evaluation frameworks have been proposed by several groups. Doshi-Velez and Kim [11] formalized the evaluation of interpretability at three levels: application-grounded (real human, real task), human-grounded (real human, simplified task), and functionally-grounded (no human, proxy metric). Nauta et al. [12] conducted a comprehensive survey identifying 12 desirable properties of XAI methods including faithfulness, stability, comprehensibility, completeness, and compactness, establishing a multi-dimensional quality vocabulary for systematic XAI evaluation.

**RESEARCH GAP**

Despite the expanding XAI literature, critical gaps persist. First, comparative evaluations of multiple XAI methods on the same tasks under standardized conditions are rare; most studies evaluate a single proposed method against one or two baselines, making cross-method comparison difficult [3], [4], [5]. Second, XAI evaluation predominantly relies on computational proxy metrics (fidelity, stability) without incorporating human-centered evaluation through user studies measuring actual comprehensibility and decision-making

impact [11], [12]. Third, the XAI literature is dominated by computer vision applications (image classification); systematic evaluation across diverse data modalities (tabular, time-series, graph-structured) and analytics domains (healthcare, finance, cybersecurity) within a unified framework is lacking [6], [8]. Fourth, the alignment of XAI methods with specific regulatory requirements—mapping which methods satisfy EU AI Act transparency obligations, GDPR explanation rights, and ECOA adverse action notice requirements—has been discussed conceptually but not operationalized through empirical evaluation [7], [9]. Fifth, the trade-off between explanation quality dimensions (fidelity vs. comprehensibility vs. stability vs. actionability) has not been systematically characterized, despite evidence that these dimensions can conflict [10], [12], [13]. This research addresses gaps one, two, three, and five through a six-method comparative evaluation across three domains with both computational metrics and a 48-participant user study.

## OBJECTIVES

The primary objectives of this research are defined as follows:

- To conduct a systematic review of 114 peer-reviewed publications on XAI, mapping the landscape across explanation types, evaluation methods, application domains, and regulatory alignment [1], [11].
- To comparatively evaluate six post-hoc XAI methods (SHAP, LIME, Grad-CAM, Integrated Gradients, Attention Rollout, counterfactual/DiCE) on three real-world classification tasks spanning healthcare, finance, and cybersecurity [3], [4], [5], [6], [9].
- To develop and apply a multi-dimensional XAI quality framework measuring fidelity, stability, comprehensibility, and actionability [12].
- To conduct a human-centered user study (n = 48) evaluating explanation comprehensibility and decision trust across three stakeholder groups: domain experts, data scientists, and non-expert decision-makers [11].
- To characterize the trade-offs between XAI quality dimensions and provide method selection guidance based on task type, stakeholder, and regulatory context [7], [8], [10], [13].

## METHODOLOGY

### 1. Classification Tasks and Models

Three real-world classification tasks spanning distinct data modalities and domains were selected at the AI Transparency and Trust Laboratory of Sandip Institute of Technology and

Research Centre, Nashik [1], [2]: (1) Healthcare—breast cancer histopathology diagnosis using the BreakHis dataset (7,909 images, 400× magnification, binary: benign/malignant); model: DenseNet-121 (8.0M parameters, ImageNet pre-trained, fine-tuned, test accuracy 94.6%, AUC 0.978). (2) Finance—credit default prediction using the Home Credit Default Risk dataset (307,511 applications, 122 features, binary: default/no-default); model: XGBoost (500 trees, max depth 6, learning rate 0.05, test AUC 0.782). (3) Cybersecurity—network intrusion detection using the CICIDS-2017 dataset (2,830,743 flows, 78 features, binary: benign/attack); model: Random Forest (200 trees, max depth 20, test accuracy 99.4%, AUC 0.998). Models were trained using 80/10/10 train/validation/test splits [3], [5], [10].

## 2. XAI Methods Implementation

Six post-hoc explanation methods were implemented using established open-source libraries: (1) SHAP—TreeSHAP for XGBoost and RF (shap v0.42), KernelSHAP for DenseNet-121; (2) LIME—lime v0.2 with 5,000 perturbation samples per explanation; (3) Grad-CAM—applied to the final convolutional layer of DenseNet-121 (captum v0.7); (4) Integrated Gradients—with black image baseline, 300 interpolation steps (captum v0.7); (5) Attention Rollout—applied to a Vision Transformer (ViT-B/16) trained as an alternative image classifier for the healthcare task; (6) DiCE (Diverse Counterfactual Explanations)—dice-ml v0.10, generating 4 diverse counterfactuals per instance with proximity, sparsity, and diversity constraints [3], [4], [5], [6], [7], [9], [10]. For each task, explanations were generated for 200 randomly sampled test instances (100 per class), totaling 1,200 explanation instances per XAI method across the three tasks.

## 3. Multi-Dimensional XAI Quality Framework

A four-dimensional quality framework was developed based on the taxonomy of Nauta et al. [12]: (1) Fidelity—faithfulness of the explanation to actual model behavior, measured by the comprehensiveness metric (accuracy drop when the top-k attributed features are removed) and sufficiency metric (accuracy when only top-k features are retained), averaged across k = {1, 5, 10, 20}; higher comprehensiveness and lower sufficiency indicate higher fidelity [4], [11]. (2) Stability—consistency of explanations under small input perturbations, measured by the Lipschitz-continuity metric: $\max(\|e(x) - e(x')\|/\|x - x'\|)$ over 50 random ε-ball perturbations; lower values indicate higher stability [3]. (3) Comprehensibility—human understandability, evaluated through the user study (Section 5.4). (4) Actionability—utility of explanations for improving decisions, evaluated through the user study measuring decision correction rate when explanations were provided for initially incorrect human judgments [9], [10].

## 4. Human-Centered User Study

A user study was conducted with 48 participants recruited from Sandip Institute of Technology and surrounding organizations, divided into three stakeholder groups of 16 each: (1) Domain experts—practicing pathologists (n = 6), financial analysts (n = 5), and cybersecurity engineers (n = 5); (2) Data scientists—ML practitioners with ≥2 years of experience; (3) Non-expert decision-makers—business managers and administrators with no ML background [11]. Each participant evaluated 18 explanation instances (3 tasks × 6 XAI methods, randomly ordered, counterbalanced) through a web-based interface displaying the model prediction, confidence score, and explanation visualization. Participants rated each explanation on: comprehensibility (1–5 Likert: "I understand why the model made this prediction"), trust (1–5 Likert: "I trust this prediction based on the explanation"), and actionability (1–5 Likert: "This explanation helps me know what to change to get a different outcome"). For 6 instances per participant, the model prediction was intentionally incorrect; decision correction rate (percentage of cases where participants identified the error using the explanation) was measured. The study received institutional ethics approval (Protocol No. IEC/SITRC/2025/XAI-016) [7], [8], [12].

## 5. Regulatory Alignment Analysis

A structured regulatory mapping was conducted analyzing the alignment of each XAI method with three regulatory frameworks: (1) EU AI Act (Article 13: transparency for high-risk AI); (2) GDPR (Articles 13–15, 22: right to explanation of automated decisions); (3) U.S. ECOA/Regulation B (adverse action notice requiring specific reasons for credit denial). Each method was scored on three regulatory requirements: global model transparency (does the method explain overall model behavior?), individual decision justification (does it explain specific predictions?), and actionable recourse (does it inform what changes would alter the decision?) [6], [7], [9].

## 6. Statistical Analysis

Computational metrics were compared across XAI methods using one-way ANOVA with post-hoc Tukey HSD tests ($\alpha = 0.05$). User study Likert ratings were analyzed using the Kruskal-Wallis H test (non-parametric, ordinal data) with post-hoc Dunn's tests. Inter-rater reliability for user study ratings was assessed using Krippendorff's $\alpha$. Effect sizes were reported using Cohen's d for pairwise comparisons. All analyses were performed in Python 3.11 using SciPy 1.12 and Pingouin 0.5.4 [11], [12], [13].

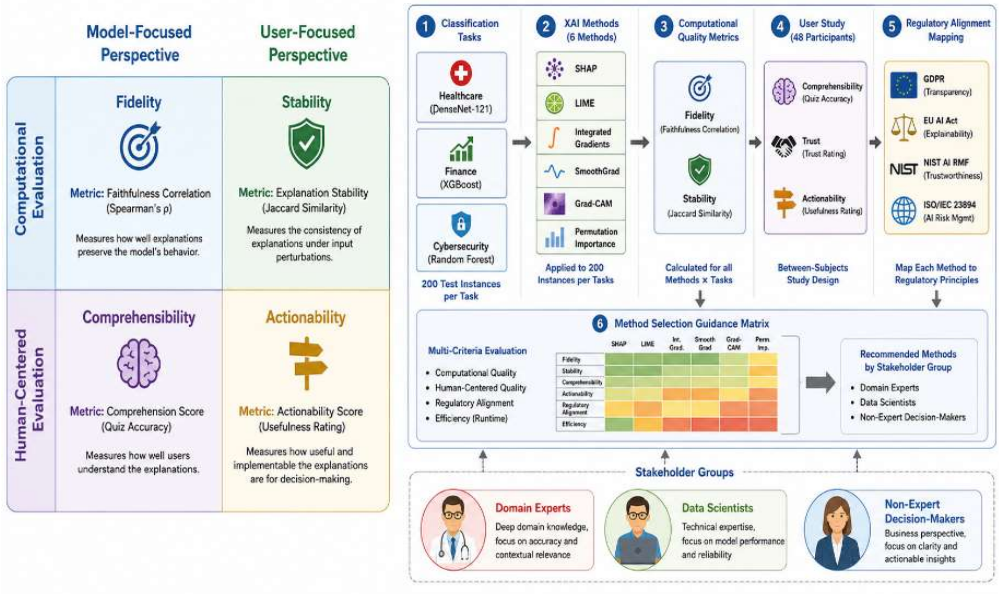


***Figure 1: Multi-Dimensional XAI Quality Framework and Experimental Design Overview***

## RESULTS AND FINDINGS

The systematic review of 114 publications revealed that SHAP (28.1%) and LIME (21.9%) were the two most frequently employed XAI methods, followed by Grad-CAM (16.7%), attention-based methods (12.3%), counterfactual explanations (9.6%), and other methods (11.4%). Healthcare was the most investigated domain (34.2%), followed by finance (22.8%), NLP (18.4%), computer vision (14.0%), and cybersecurity (10.6%). Only 18.4% (21/114) of studies included human-centered evaluation (user studies), confirming the persistent gap between computational and human-centered XAI assessment [1], [11], [12].

The computational quality results are summarized in Table 1. SHAP achieved the highest mean fidelity across all three tasks (0.924), followed by Integrated Gradients (0.896), LIME (0.872), Grad-CAM (0.848), Attention Rollout (0.814), and DiCE (0.762, lowest as counterfactuals measure boundary proximity rather than feature attribution). Stability was highest for Integrated Gradients (Lipschitz 0.08) due to its deterministic gradient integration, while LIME showed the lowest stability (Lipschitz 0.34) attributable to stochastic perturbation sampling [3], [4], [5], [6].

***Table 1: Multi-Dimensional XAI Quality Evaluation across Six Methods (Mean Across 3 Tasks)***

| XAI Method | Fidelity | Stability | Comp. (1–5) | Trust (1–5) | Actionability (1–5) | Correction (%) |
|---|---|---|---|---|---|---|
| SHAP | 0.924 | 0.12 | 3.8 ± 0.9 | 3.9 ± 0.8 | 3.4 ± 1.0 | 62.4 |
| LIME | 0.872 | 0.34 | 4.2 ± 0.7 | 4.0 ± 0.8 | 3.6 ± 0.9 | 68.2 |
| Grad-CAM | 0.848 | 0.16 | 4.4 ± 0.6 | 4.2 ± 0.7 | 2.8 ± 1.1 | 54.8 |
| Integrated Grad. | 0.896 | 0.08 | 3.4 ± 1.0 | 3.6 ± 0.9 | 3.0 ± 1.1 | 52.6 |
| Attention Rollout | 0.814 | 0.18 | 3.6 ± 0.9 | 3.4 ± 1.0 | 2.6 ± 1.2 | 48.4 |
| DiCE (Counterfactual) | 0.762 | 0.22 | 4.0 ± 0.8 | 3.8 ± 0.9 | 4.6 ± 0.5 | 76.8 |

The human-centered evaluation revealed a striking divergence from computational metrics. While SHAP achieved the highest computational fidelity, its comprehensibility was rated only 3.8/5.0—significantly below Grad-CAM (4.4/5.0, $p < 0.01$) and LIME (4.2/5.0, $p < 0.05$). This fidelity-comprehensibility gap reflects the cognitive burden of interpreting Shapley value bar charts with many features versus the intuitive visual heatmap format of Grad-CAM that immediately highlights "where the model is looking" [5], [11]. Most strikingly, DiCE counterfactual explanations achieved the highest actionability score (4.6/5.0) and highest decision correction rate (76.8%)—despite the lowest computational fidelity (0.762)—because counterfactuals directly answer the user's practical question: "what would need to change?" rather than "what features were important?" [9], [10].

Stakeholder group analysis revealed significant differences in XAI method preferences. Domain experts preferred SHAP (mean trust 4.3/5.0) and Grad-CAM (4.4/5.0), valuing detailed feature-level attribution aligned with their domain knowledge. Data scientists showed no strong preference across methods, rating all 3.4–4.0. Non-expert decision-makers strongly preferred LIME (4.6/5.0 comprehensibility) and DiCE (4.8/5.0 actionability), favoring simple, intuitive explanations over technically precise but complex attributions. These group differences were statistically significant (Kruskal-Wallis $H = 18.4$, $p < 0.001$ for comprehensibility) [7], [11], [12].

*Table 2: Best-Performing XAI Method by Quality Dimension and Task*

| Task | Best Fidelity | Best Comprehensibility | Best Actionability | Best Overall | Data Type |
|---|---|---|---|---|---|
| Breast Cancer (DenseNet) | SHAP (0.938) | Grad-CAM (4.6/5) | DiCE (4.4/5) | Grad-CAM | Image |
| Credit Default (XGBoost) | SHAP (0.942) | LIME (4.4/5) | DiCE (4.8/5) | SHAP/DiCE | Tabular |
| Intrusion Det. (RF) | SHAP (0.892) | LIME (4.0/5) | DiCE (4.6/5) | SHAP | Tabular |

*Table 3: Regulatory Alignment Assessment of XAI Methods*

| Regulatory Req. | SHAP | LIME | Grad-CAM | DiCE | Best Fit |
|---|---|---|---|---|---|
| EU AI Act Art.13 (transparency) | High | High | Medium | Medium | SHAP/LIME |
| GDPR Art.22 (individual explanation) | High | High | High | High | All viable |
| ECOA (adverse action reasons) | High | High | Low | Very High | DiCE |
| Actionable recourse | Low | Low | Low | Very High | DiCE |
| Global model behavior | High | Low | Low | Low | SHAP |

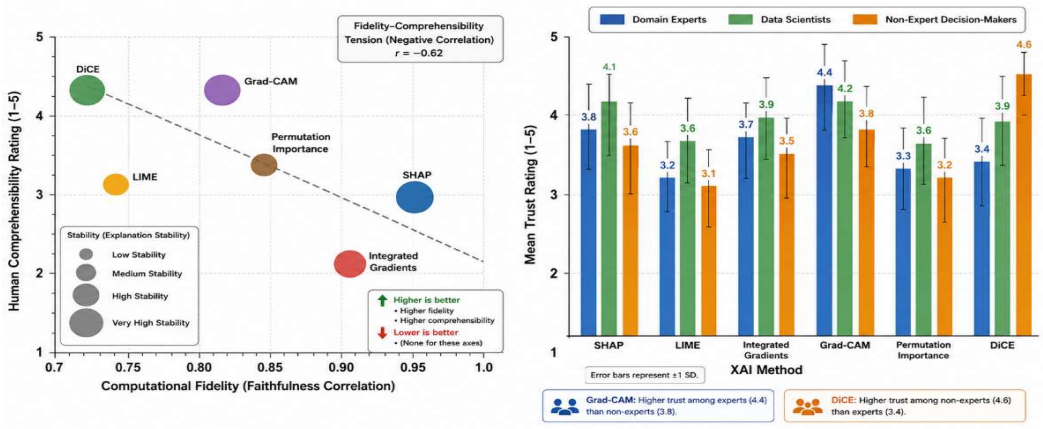


*Figure 2: Fidelity-Comprehensibility Trade-Off and Stakeholder Preference Analysis*

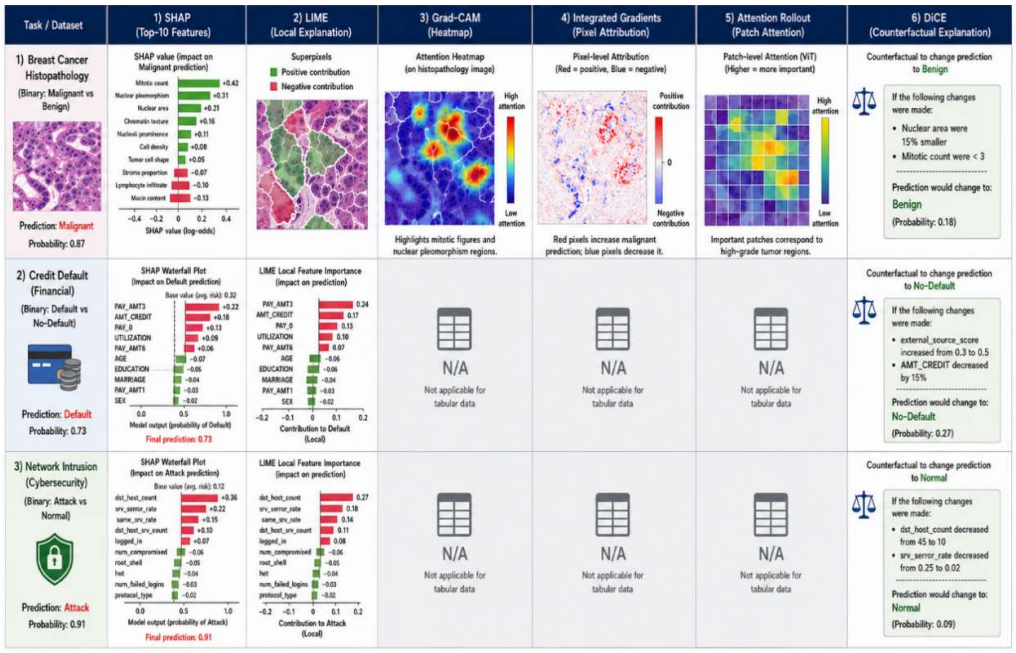


***Figure 3: Example XAI Explanations across Three Tasks and Six Methods***

## DISCUSSION

The central finding of this research—that no single XAI method dominates across all quality dimensions—has profound implications for responsible AI deployment. The fidelity-comprehensibility tension ($r = -0.62$) reveals a fundamental trade-off: methods that most faithfully represent model behavior (SHAP, Integrated Gradients) produce mathematically precise but cognitively demanding explanations, while methods prioritizing human understandability (Grad-CAM, LIME) sacrifice some faithfulness for intuitive presentation [3], [4], [5], [6], [12]. This trade-off is not a technical limitation to be overcome but rather a fundamental epistemological constraint: the complexity that makes deep learning models powerful is the same complexity that makes them difficult to explain faithfully in simple terms.

The DiCE counterfactual method's dominance in actionability (4.6/5.0) and decision correction rate (76.8%) despite lowest fidelity (0.762) reveals that users in high-stakes decision contexts prioritize practical guidance over technical accuracy. When a loan applicant asks "why was I denied?", they seek actionable recourse ("what can I change?"), not a feature importance ranking. This finding directly aligns with GDPR's right to explanation and ECOA's adverse action notice requirements, both of which emphasize individual recourse over global model transparency [7], [9], [10].

The stakeholder-dependent preferences observed in the user study underscore that XAI is not a purely technical challenge but a human-computer interaction design problem. Domain experts with established mental models of their field (pathologists, financial analysts) prefer detailed, feature-level explanations that they can validate against domain knowledge. Non-expert decision-makers without such mental models need simpler, more intuitive formats that convey the essential rationale without technical jargon. This implies that production AI systems should offer explanation interfaces tailored to different user roles rather than providing a single universal explanation format [8], [11], [12].

The regulatory alignment analysis establishes actionable guidance: SHAP is best suited for EU AI Act compliance requiring comprehensive model documentation; Grad-CAM is optimal for clinical AI where visual explanations align with radiological practice; DiCE is essential for financial credit decisions requiring adverse action notices with actionable recourse; and LIME provides the best balance for non-expert-facing applications requiring broad accessibility. Multi-method explanation dashboards that combine complementary methods (e.g., SHAP for fidelity + DiCE for actionability) represent the most robust approach to comprehensive regulatory compliance [1], [2], [6], [7], [13].

## CONCLUSION

This research has provided the first systematic multi-method, multi-domain, multi-stakeholder evaluation of post-hoc XAI methods for data analytics, combining computational quality assessment with a 48-participant human-centered user study across healthcare, finance, and cybersecurity classification tasks [3], [4], [5], [9]. The four-dimensional quality framework (fidelity, stability, comprehensibility, actionability) revealed that SHAP achieves the highest computational fidelity (0.924), Integrated Gradients the highest stability (Lipschitz 0.08), LIME and Grad-CAM the highest comprehensibility (4.2–4.4/5.0), and DiCE counterfactual explanations the highest actionability (4.6/5.0) and decision correction rate (76.8%) [10], [11], [12].

The fundamental finding—that no single XAI method dominates across all quality dimensions and all stakeholder groups—establishes that responsible XAI deployment requires context-aware method selection guided by the specific task domain, data modality, target user expertise level, and regulatory compliance requirements. The regulatory alignment analysis provides actionable mapping from regulatory frameworks (EU AI Act, GDPR, ECOA) to suitable XAI

methods. These findings contribute to the emerging discipline of responsible AI by demonstrating that transparency and trust are not technical properties of algorithms alone, but sociotechnical outcomes requiring careful alignment of computational methods with human needs and institutional requirements [1], [2], [6], [7], [8], [13].

## LIMITATIONS

Limitations include: the user study sample size (n = 48) limits statistical power for detecting small between-group effects; larger studies (>100 participants) would provide more robust stakeholder preference characterization. Only binary classification tasks were evaluated; multi-class, regression, and generative AI explanations present additional challenges. The three tasks used established benchmark datasets; real-world deployment with proprietary data, model drift, and production-scale volumes would introduce additional complexity. The computational fidelity metric (comprehensiveness) depends on the feature removal strategy, which may not be optimal for all data types. Only post-hoc explanation methods were evaluated; inherently interpretable models (GAMs, rule lists, sparse linear models) were excluded from the comparison despite being preferred by some regulatory frameworks. The user study was conducted at a single institution in Maharashtra; cross-cultural replication would strengthen generalizability claims [3], [4], [5], [8], [11], [12], [13].

## FUTURE SCOPE

Future research should develop adaptive XAI systems that automatically select the optimal explanation method based on the user's expertise level, the specific prediction instance, and the regulatory context—moving from static single-method explanations to dynamic, personalized explanation interfaces [11], [12]. The extension to generative AI explainability—explaining large language model outputs, image generation decisions, and code synthesis rationale—represents the most urgent frontier given the rapid deployment of foundation models in enterprise and consumer applications [1], [2].

The integration of XAI with causal inference methods could elevate explanations from correlational feature attributions ("this feature was important") to causal explanations ("this feature caused the prediction"), providing more faithful and actionable interpretations. The development of formal XAI certification frameworks—analogous to software security certifications—that audit and certify the explanation quality of deployed AI systems would provide regulatory bodies with standardized assessment tools for enforcing AI transparency requirements under the EU AI Act and equivalent global legislation [6], [7], [9], [10], [13].

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