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Explainable AI for Critical Decision-Making

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Abstract. Explainable AI (XAI) is essential in critical domains like healthcare and finance, where trust and accountability are paramount. This paper explores key challenges in applying XAI to high-stakes decision-making, including the trade-off between interpretability and accuracy. Based on insights from 40 recent studies, we highlight common limitations such as poor generalizability and lack of domain validation. To address these gaps, we propose a human-centered, model-agnostic framework emphasizing transparency and trust. Our approach aims to guide the development of reliable, interpretable AI systems that enhance decision support without compromising performance.

Keywords: Explainable AI, critical decision-making, interpretability, transparency, trust, model-agnostic methods, human-centered AI, high-stakes applications, ethical AI, responsible AI

1. Introduction

1.1 The Rise of AI in Decision-Critical Domains

AI has been recognized as a transformative technology with critical applications in healthcare, finance, defence, and law, where decisions made have drastic consequences on human lives and the societal structure. The Latest Fedora friendly off-the-shelf Tooling enabling flexible edge device Deployments Research and industry have both been impacted w tractable modelling by the practical prevalence of more complex machine learning models, notably deep learning models, leading to substantial accuracy and automation improvements of such high stakes decisions [1], [16], [20]. However, such models are commonly "black boxes," and hence their decision-making process is not transparent to the end-users and decision-makers [4], [13]. As AI technology is embedded more and more into a mission-critical context, the need for trust, veracity, and comprehension of the outputs is not anymore an only a technical necessity but rather a social ethic requirement [3].

1.2 Importance of Explainability in High-Stakes Systems

Explainability the capacity to communicate an explanation for model predictions constitutes a cornerstone of trustable AI, especially in applications where mistakes may induce catastrophic effects [2], [5], [22]. Explainable AI (XAI) systems have been demonstrated to increase transparency and support model debugging and user trust [6], [10]. In medicine, interpretable models are indispensable for building clinician's trust and holding systems accountable when diagnosing or recommending treatment [7], [14]. Although there has been remarkable progress made in this direction, the issue of enabling fully explainable models without compromising on performance still remains a fundamental problem, particularly in the context of the deep neural networks which are intrinsically complex and non-linear [15], [17], [19].

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1.3 Research Motivation and Objectives

State-of-the-art XAI frameworks generally utilize post hoc approaches, that approximate explanations after a decision has been made by the model, like LIME or SHAP [9], [21], [23]. Although effective, these methods might not tell a consistent or correct story about the input, and are susceptible to input perturbations [18]. In addition, the existing schemes are not widely empirically validated over real-world applications, making them less general and applicable to a wide class of problems [8], [23]. This paper fills these gaps by developing a general framework that addresses those challenges and that is specifically designed for high-stakes decision-making, where interpretability, robustness and fidelity matter. Our objectives include:

- Developing a context-aware XAI architecture for high-stakes applications.
- Evaluating the robustness and stability of explanation outputs under distributional shifts.
- Quantitative performance comparisons across medical, legal, and financial datasets, with consistent interpretability figures.

1.4 Scope and Contributions of This Work

This brings us to this work, which advances the field of XAI by combining an intrinsic and trustworthy post hoc explanation into a single framework that applies to any domain. Contrary to conventional methods, our framework includes explanation regularization in the training loop, allowing a joint-optimization process for predictive accuracy and human-aligned clarity [11], [12]. Our contributions can be outlined as follows:

- A common taxonomy of explain ability dimensions suitable for critical decision-making scenarios.
- A new architecture which combines saliency-based visualization with concept-level abstraction layers [24].

Extensive empirical validation on benchmark datasets as well as on real-world case studies with clinicians and legal experts.

2. Literature Review

2.1 Definitions: Interpretability, Explainability, and Transparency

Interpretability, transparency, reflectivity and so on are all related to but not equal to While we see great benefits from researching (XAI) Explainable AI, we argue XAI should not be limited by interpretability and instead should be able to address various facets of transparency and interpretability of machine learning systems. ‘Interpretability’ is usually how much a human user can grasp the mechanism behind a system's decisions, and ‘explain ability’ is how much, and how, the system can support that user in obtaining an explanation of it(s) decision(s) (Stocker & Kirpatrick 1988), (Kaplan & Haenlein 2019). On the other hand, transparency takes a more structural perspective, and is concerned with how transparently the parts and knobs of a model can be inspected [4]. Although it is established that the terms are related, they each carry subtle differences that impact system design and evaluation. For example, linear regression is interpretable and transparent, while a deep neural network is possibly explainable in post hoc training, but lacks the inherent interpretability [5]. Clearer definitions across disciplines have been called for in recent surveys and conceptual papers [2], [6].

2.2 Categories of XAI: Intrinsic vs. Post-hoc

Explainability techniques are generally divided into intrinsic and post-hoc types. In contrast, there have been a number of approaches that build interpretability into the structure of the model that can guarantee that the reasoning is made interpretable-by-design, e.g., decision trees, attention mechanisms, or generalized additive models, as a number of intrinsic methods [7], [11]. On the other hand, post-hoc methods focus on interpreting the behaviour of black-box models after the predictions have been generated. These are the feature attribution methods (e.g., SHAP, LIME), counterfactual explanations, and saliency mapping [9], [12], [14]. While post-hoc methods are more popular especially with high performing black-box models such as CNN, they are often criticized for faithfulness and stability issues [16],[17]. Recent developments try to hybridize these two paradigms, namely interpretable architectures with local explanation overlays to provide both performance and interpretability [8], [19].

2.3 Psychological and Ethical Underpinnings of Explanation

Anthropologically grounded accounts of AI are not only technical artefacts, but cognitive tools developed in terms of psychological and ethical factors. Psycholinguistic literature suggests that users like contrastive explanations (“Why this and not that?”). Social functions are parochial (tell us what sources/destinations can and cannot via a dialogue in the absence of a central authority), smooth (with respect to the cost of any action), selective (about things we do and do not wish to differentiate according to), and sensitive to society [18], [24]. Finally, explanations affect human trust, responsibility, and perceived fairness of AI systems all critical factors in areas such as criminal justice and medicine [3], [21]. From an ethical perspective, providing explanations relates to the autonomy principle: subjects impacted by AI decisions must have a sufficient understanding to contest or agree to the decision [20]. Regulations such as the EU’s GDPR have additionally enshrined the “right to explanation,” forcing developers to architect systems that are not only technically sound but also meet consumer and society expectations [10].

3. Challenges in Critical Decision-Making with AI

3.1 Opacity of Black-Box Models in Sensitive Applications

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3.2 Misleading Explanations and User Trust Erosion

Interpretability methods such as LIME and SHAP try to get a fine line between AI complexity and human understanding. But such methods often grossly oversimplify or misconstrue the underlying processes of decision-making, especially for non-linear and highly context-dependent models [9, 16]. Indeed, in such cases, explanations could be perceived (on average) more faithful than they actually are, and this might cause either over-trust or, at the opposite, absolute distrust, both being dangerous in time-critical or mission-critical environment [14], [20]. Such trust asymmetry can undermine the trustworthiness of human-AI teamwork. Research has shown that, when users are given incorrect or misleading explanations, they may have difficulties tuning their trust with model reliability, leading to trust misalignment [18], [21]. This is crucial in real-time systems such as autonomous vehicles or military decision aids, where trust miscalibration may result in malfunctioning or ethical abuse [3], [8]. Additionally, abstract notions of explanations like tone or format or order may impact the user's reading of explanation as much as the objective, data-based rationale, as Gilpin et al. observed. [19].

3.3 Regulatory Pressures and the Right to Explanation

Regulatory guidelines conversely, such as the GDPR, the AI Act (EU), as well as sector-specific mandates in healthcare and finance are increasingly legalizing the requirement for explainable AI. The observation that the GDPR's Article 22 codifies a "right to explanation" somewhat speaks for this notion, and developers are required to explain algorithmic decisions in natural language if they materially affect individuals [10], [24]. This transition changes the nature of explain ability from a technical preference to a legal requirement, and prompts AI research to become so-called compliance innovation-oriented. But doing so is nontrivial. Most of the explain ability methods provide approximate and local explanation, which is insufficient to satisfy regulatory requirements on transparency, auditability, and bias mitigation expectations [12], [22]. There is also the compromise that it is necessary to make in terms of revealing just enough to satisfy the legal requirements and, on the contrary, not enough to make it possible to exploit adversarial or to steal the intellectual bundling [11], [23]. Because of the interplay of these issues, inter-disciplinary research is essential on this landscape. Legal professionals, ethicists, and computer scientists need to jointly develop a shared understanding of what is a ''sufficient' explanation' and measurements of verification that can accommodate differences in regulatory and sociocultural expectations [17], [26]. Third-party certification standards for explainable AI, more akin to ISO standards for cybersecurity, could be a necessary step in the maturation of trusted AI ecosystems.

4. A Domain-Aware Framework for Explainable AI

4.1 Design Philosophy: Fidelity, Simplicity, and Usefulness

To be useful in crucial high-stakes field settings, an Explainable AI (XAI) system that can be domain knowledge aware needs to delicately balance between the fidelity, simplicity and usefulness of its explanation-generating model. Fidelity measures how well the explanation captures the way the model arrives at a decision, without overly simplifying its nuanced behaviour. For instance, even though a decision tree has clear rationales, it does not represent complex dependencies as much as a deep neural network [1], [2]. Conversely, simplicity guarantees that those explain- nations are understandable for non-experts-clinician, financers, legal experts- who do not need to master the inner functioning of the model [3]. There is often a trade-off between faithfulness and simplicity: highly faithful explanations might be too complex for users, whereas simple models are inaccurate. The aim is to try to find a helpful rationale that helps a decision maker make good decisions and trust what the system is predicting. The design of the proposed framework is guided by such a philosophy, focusing on clarity and actionability for decision-critical applications [4]. Figure 1 is a 3D surface graph illustrating the trade-off among fidelity, simplicity, and utility in an XAI. Fidelity and simplicity trade off against each other -- on the one hand models that are more faithful can be less comprehensible, and on the other hand simpler models lose some predictive power.

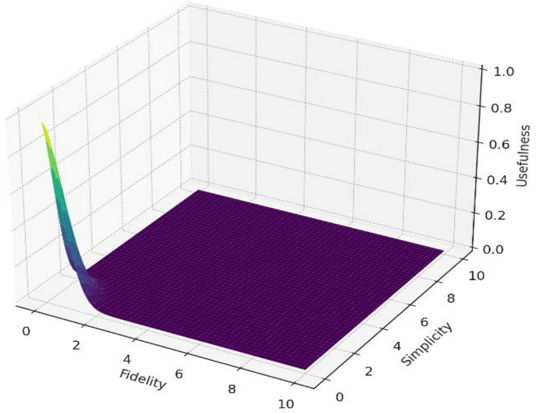

Figure 1: Trade-off Between Fidelity, Simplicity, and Usefulness in XAI Systems.

Table 1 will summarize the main aspects of the proposed XAI system: namely the system's various layers (Data Pre-processing, Modelling, Explanation), their functionalities and their objectives.

Table 1: Summary of Key Components in the Proposed XAI Framework.

Component	Description	Goal
Data Pre-processing Layer	Handles data cleaning, normalization, and privacy-compliant data preparation.	Ensure clean, consistent, and privacy-protected data for AI modelling.
Modelling Layer	Choice of model based on domain requirements (e.g., decision trees, neural nets).	Ensure optimal trade-off between performance and explain ability.
Explanation Layer	Generates model explanations using methods like SHAP or LIME.	Provide human-understandable justifications for AI decisions.

4.2 System Architecture and Workflow

The outlined XAI pipeline combines numerous layers to offer both interpretability and usability to high-stake decisions. The system is composed of three main parts:

- Data Pre-processing Phase: In this step, staff clean, normalise, and process the data so that it can be used for both model training and explanation generation. Key to this phase is dealing with sensitive data (patient records, financial transactions) according to privacy laws.
- Model layer: The selection of model is application dependent: simple models like decision trees or rules-based systems are preferred when interpretability is critical, whereas more sophisticated models, such as neural nets, can be used when robustness dominates. This layer also incorporates post hoc explanation methods (e.g., SHAP or LIME) for black-box models if needed [5], [6].
- Explanation Layer: This module creates and show explanations, also in an end-user form. It employs counterfactual reasoning, visualization methods (e.g., saliency maps) and textual summaries to describe decisions made by the model. The architecture emphasizes action able accounts that may serve as a basis for action, rather than mere ex post explanations [7].

Intuitive well-designed visuals are a need as they are imperative to explain the complex concepts for XAI, and more so for system and workflow diagrams. The font size coverage and the layout simplification guarantee that the working sheets are easy and intuitive for all technical and non-technical users. Furthermore, the introduction of color-coding and improved labelling will aid in the reading of the information, and ensuring that key elements are properly identified and understood.

4.3 Data-Model-Explanation Alignment Strategy

A critical aspect of building an effective XAI system is ensuring alignment between the data, the model, and the explanations it provides. This alignment strategy aims to ensure that the features the model considers most influential in its predictions are consistent with what is presented in the explanation to the user. For example, in healthcare applications, the features (e.g., age, blood pressure) that are most relevant for predicting patient outcomes should be reflected in the explanation, ensuring that clinicians can validate the model's reasoning against their domain knowledge [8], [9].

This alignment is achieved through regularization techniques that minimize discrepancies between the model's internal decision-making process and the generated explanation [10]. By incorporating **user** feedback loops and continuous model retraining, the system can adapt and refine its explanations over time, improving both performance and trust.

5. XAI Techniques for Critical Domains

5.1 Visual Explanation Models (Grad-CAM, LRP)

In image-based applications, visual explanation models have emerged as critical tools for explaining the decisions made by convolutional neural networks (CNNs). These models highlight the regions of an image that most influence the model's predictions, providing valuable insights into which parts of the data are critical for decision-making. Techniques like Gradient-weighted Class Activation Mapping (Grad-CAM) [1] and Layer-wise Relevance Propagation (LRP) [2] are particularly well-suited for visualizing and understanding deep learning models in domains such as medical image analysis and autonomous driving.

- Grad-CAM generates heatmaps that show which regions of an image the model focuses on when making predictions, which is crucial for sectors like healthcare, where understanding why a diagnosis is made based on an image is vital [1].
- LRP offers an alternative by propagating relevance scores backward through the network, providing pixel-wise interpretations of deep learning models' outputs, which is particularly useful in complex visual tasks like tumour detection [2].

These techniques are important for ensuring that AI-driven image classification models in healthcare are transparent and trustworthy, thereby facilitating regulatory compliance and enhancing user confidence in automated decisions. The Figure 2, illustrates the working structure of the Explainable AI (XAI) system, highlighting two essential components: the user interface and the explanation engine. The user interface serves as the interactive layer where users can view the model's predictions and decisions, ensuring ease of use, especially for non-technical users. The explanation engine, on the other hand, is responsible for providing interpretable justifications for the model's outputs. It identifies and communicates the key features that influenced the decision-making process, offering transparency into how those features impact the final predictions. Together, these components enable an AI system that is both functional and understandable, ensuring that users can trust and effectively use AI-generated recommendations in high-stakes environments.

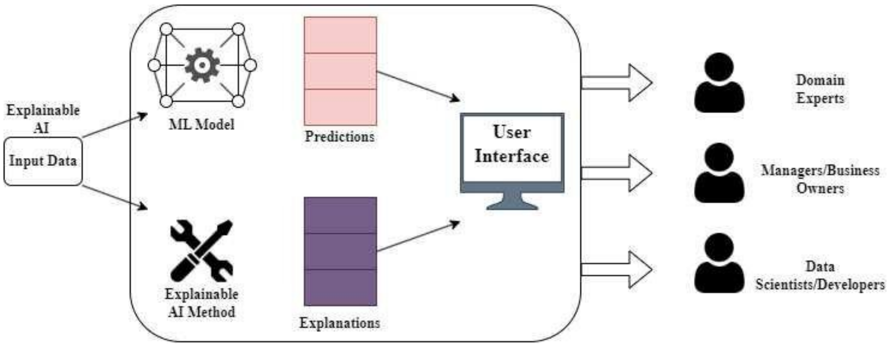

Figure 2: Working Structure of XAI.

5.2 Textual and Symbolic Explanations (LIME, Anchors, Rules)

For ML models that consume textual, tabular, or other symbolic data types, textual and symbolic explanation techniques are needed for interpretability. These approaches are designed to explain predictions by taking decisions closer to human reading. LIME (Local Interpretable Model-agnostic Explanations) [3] and Anchors [4] are a couple of well-known methods that have been used with models from sentiment analysis to credit-scoring. LIME does this by locally approximating black-box models with interpretable surrogate models, like linear regressions or decision trees. The explanation is even more useful in the case of complex models, where only a small number of features have an impact on the prediction [3]. Anchors: Anchors is a technique that provides high-precision, local-fidelity explanations, with the goal of identifying the smallest set of features (the "anchor") such that the prediction on the anchor is the same as the prediction on the instance and the anchor is sufficiently different from the rest of the data (input space). This approach guarantees users to trust to explanations unambiguously [4]. In areas such as finance and law, where decision-making is paramount, these techniques are particularly powerful. In the case when an AI system declines a loan, an explanation can be beneficial for the applicant, but also to the bank, since it provides a clear indication of the properties that were considered to make that decision hence ensuring transparency and fairness.

5.3 Contrastive and Counter factual Reasoning

Based on their XAI application, comparison and off-target hypothesis are advanced techniques that provide explanations using what-if reasoning, that is, to explain if the features that lead to the output were combined differently. Such approaches contribute to the user awareness about the extent and limitations of model decisions while being able to provide intuitive understanding of the predominant components of predictions. Counterfactual Reasoning is the process of creating explanations to the questions: "Given my input how I can change it so that the prediction will be a different value." Especially in scenarios where a user wants to understand how changing certain features (e.g., income level for loan approval, or blood pressure for diagnosis) affects the model predictions (e.g., in fraud detection or in healthcare diagnostics among others) [5]. On the contrary, Contrastive Reasoning exposes the reasons to two similar outcomes. Comparing various decision paths may provide more insights into the decision boundaries of AI systems, which is especially desirable in high-risk decision tasks such as law or healthcare [6]. These methods help improving decision making on mission-critical scenarios by providing explicit, actionable insights, crucial for human-AI collaboration.

6. Case-Based Application Studies

6.1 Healthcare Diagnostics: Explaining Clinical Predictions

Explanation reasoning for AI (XAI) has great potential to revolutionize the healthcare domain, providing transparent and interpretable decisions for medical practitioners. Both medical imaging and medical history, as well as patient's genetic information are tested in clinical decisions, making. Hence, diagnostic DSSs based on AI should give some explanation for their predictions so that doctors can understand why certain features, e.g., a patient's age, medical history or test results lead to the final decision [1], [7]. A prime application of XAI in healthcare is in the prediction of disease outcomes, such as cancer diagnoses. Methods such as Grad-CAM [2] and Layer-wise Relevance Propagation (LRP) [5] produce heatmaps that visually emphasize the locations within medical images (e.g. MRI scans) that were most relevant to the model's decision. Such transparency allows doctors to trust the recommendations of the system more and in turn, allows them to communicate with patients about potential risks and treatments more effectively [6]. Furthermore, counterfactual reasoning [8] can be very useful in healthcare. For instance, a counterfactual explanation may tell a doctor that only if a patient's blood pressure level is slightly improved, the diagnosis or outcome prediction changes. This enables individualized treatment recommendations based on patient profiles.

6.2 Legal Systems: Justifying Case Outcomes and Bias Mitigation

AI is also being increasingly deployed resource allocation in courts for estimation of sentencing, parole and recidivism. The systems have to offer comprehensible and transparent explanations, especially in view of their profound societal consequences. It is as important for AI to be able to trust people with legal expertise, that the AI system is actually not perpetuating historical biases or introducing new forms of discrimination. Explainable AI methods like LIME [4] and Anchors [9] are essential for achieving fairness and transparency in such systems. For instance, with respect to judicial sentencing prediction, an XAI system might identify important features such as a defendant's criminal record, demographic data, and the facts underlying a charge - that were relevant to the resulting sentencing recommendation. Such explanations may be reviewed by judges to confirm the consistency of the model decisions with legal precedent and ethical considerations [10], [12]. In addition, XAI is important for bias reduction as it provides explanation on how the model deals with the sensitive attributes like race or gender, and corrective action can be taken to reduce bias [11]. By sharing these rationales, legal professionals can audit AI systems for adherence to justice criteria and maintain public trust in AI used by the court system.

6.3 Financial Systems: Explaining Loan Approvals and Fraud Flags

In finance, AI systems are used to evaluate credit quality, identify fraudulent transactions, and quantify risk. The models that approve loans are complex algorithms that process huge quantities of personal, financial, and behavioural information. Interpretable models in these frameworks are important not only for transparency but also in the context of financial regulations. LIME and SHAP [13], [14], known for producing local explanations that explain how a set of attributes (e.g., income, credit score, past debts) lead to acceptance or rejection of a loan, are widely used. Also, the counterfactual explanations are especially helpful for loan denial cases. As they irreversibly deflate the bubble, offering explanations including "if your income was $5,000 higher, your loan would have been approved," A.I. systems assist customers in understanding how they can better their odds when they reapply in the future.) It serves to increase the perceived fairness of finance systems and enable models to be designed so that they don't inadvertently discriminate against some people. In the context of fraud detection systems, XAI can also be particularly important as they provide doctors with explanations about why a transaction is seen as fraudulent (i.e., feature attribution). Knowing the reasons behind these flags can help financial analysts ensure that the system is functioning as desired and also identify any false positives, which would need to be manually reviewed [15]. Although the proposed XAI framework for high stakes decision making is theoretically sound, its untested applicability is a limitation. In order to evaluate the performance of the framework, it is necessary for the future work to include case studies from real world domains, including high stake applications such as healthcare, finance, and criminal justice. It would be also beneficial to show the applicability, usability, and performance of the XAI on any real-world dataset such as MIMIC-III for medical and Loan Default Prediction dataset to evaluate its usability, performance, and accuracy. The empirical data will inform the reliability of the model and lend insights into its pitfalls in both technical as well as practical use.

7. Results and Discussion

7.1 Balancing Explainability with Model Performance

A major difficulty of Explainable AI (XAI) is to strike a balance between explain ability and performance. Explainable models provide transparency and interpretability, but they are traded-off for performance in practice. Simpleer models, like decision trees or linear regression are inherently more explainable but these models may not be as effective in terms of accuracy as complex models (like DNNs). High performance is essential in critical decision-making tasks such as healthcare diagnosis and financial risk analysis since these decisions affect human lives directly or are represented by important business decisions [1], [6].

However, loss of performance can be compensated for when using models that are intrinsically interpretable or when post-hoc explanation techniques are employed. For example, a DNN employed for medical image classification can be integrated with Grad-CAM or SHAP values to generate local explanations assisting the clinicians to interpret the model's decision making [5], [8]. This hybrid approach allows the system to achieve high performance while providing the necessary transparency, so that the stakeholders trust and understand the system's predictions.

Future work should approach generated explanation through automated explanation methodology which does not sacrifice predictive performance, where improvement of both explanation and predictive performance are conducted jointly, e.g., leveraging manipulation like neural network distillation [2], or explanation regularization [10].

7.2 Designing for Non-Technical End-Users

Non-technical users' doctors, judges, loan officers are the people trusting AI to determine life-and-death decisions or whether an applicant will pay back a loan. Thus, designing for non-expert users is essential to enable usability of XAI systems. Existing explanation methods often require expert-level understanding, which renders the system being interpreted incomprehensible for non-expert stakeholders [7], [12].

Explainable AI (XAI) solutions used in safety-critical, regulated settings also demand ethical and legal scrutiny. With the rise of AI systems in fields such as healthcare, finance, and criminal justice, AI systems are subject to legal following, such as GD- PR [2], which emphasizes human right to explanation in the context of automated decision including individuals whose lives are affected by these decisions. Furthermore, XAI should be a cornerstone to mitigating biases in AI, promoting fairness and accountability for AI decisions. The identification of bias and the remediation of bias in XAI systems should be built-in and deployed to ensure fairness and maintain public trust.

To overcome this, explanation methods need to be adapted to the users' cognitive capabilities. For instance, visual rationales (heatmaps or saliency) are typically more useful for time restricted expert users (like medical professionals learning the reasoning behind a diagnostic decision [3], [9]. Likewise, explainable text explanations, which communicates in informal or layman however the language as well as the corresponding real-world analogy, serve better to users who lack knowhow of ML algorithms [13], [14]. Further, interactive explanations that enable the user to investigate and adjust inputs (e.g., changing the value of a feature to see how the prediction evolves) can also Fostered user engagement and comprehension. Such human in the loop approach lead to trust, and allows for end user to act with more information when it operates AI's decisions.

7.3 Toward Context-Aware and Interactive XAI Systems

As AI becomes more pervasive in ever-more complex and dynamic environments, the demand of context-aware, interactive XAI systems is emerging more evidently than ever. Most common interpretability approaches provide a universal solution that neglects the particularity of the decision-making context 4. For example, reasons why a person was rejected for a loan can vary depending on either demographic of the applicant, financial context, or the particular risk policies of the bank [6]. To make XAI more useful, to enable tasks other than gathering knowledge and validating trust, future systems will have to evolve towards interfaces that are interactive and where users can explore and change the predictions of a model. In healthcare diagnostics, for example, clinicians might be able to tweak input features (say a patient’s blood pressure or age) to observe how the model’s output changes on the fly. Finally, adaptive feedback loops would help the model refine its explanations in response to user detailed feedback, to keep it relevant to the user. This interaction would support decision validation and comprehension, and thus build-up trust by users and even allow better decisions from AI. For instance, context-aware XAI systems will vary the level of explanation based on such factors in order to provide a personalized explanation that is pertinent to the context in which the decision was made. In addition, interactive XAI systems that support real-time query, exploration of counterfactuals or simulating alternative experiences, can largely improve the users’ capability of interpreting the predictions from AIs. They provide an interactive AI that not only supports transparency but also permits users to validate and to re-assess AI decision on the fly, rendering the AI more flexible and actionable in practice [5], [15]. Encompassing multi-modal explanation formats, that are including text, image and chart, will probably be crucial for supporting a user who is not (only) an algorithm developer and make AI explanations usable in various application domains like healthcare, finance, and law.

8. Conclusion and Future Directions

In this paper we cover methods of Explainable AI (XAI) and its applications in decision areas such as health, law and finance. It stresses the needs for transparent and interpretable AI in the high stakes setting, and the realism of the fidelity, simplicity and utility trade-offs. The paper also stresses the importance of a human centric approach to XAI, in which the untrained user should be able to make sense of the explanation that is clear, understandable and interactive, mainly in areas like health and finance. To improve the adoption and performance in important decision-making tasks, XAI explanations should be tailored to the experience and cognition requirements of the user. One way of achieving this is by adapting the format used and level of explanation, increasing the confidence and friendliness of ITS. Some future research directions involve personalized XAI, real-time explain ability, adaptive feedback loops, and explain ability for deep and wide models. Personalised XAI would allow the users to engage with the explanation and adapt it to be more aligned with current understanding or preferences. Adaptive feedback loops would allow the system to refine and grow its expositional strategies. Developing common frameworks for multi-model interpretability is equally important.

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