# From Questions to Insights: Exploring XAI Challenges Reported on Stack Overflow Questions

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## ABSTRACT

Lack of interpretability is a significant barrier that hinders the practical integration of Artificial Intelligence (e.g., Machine Learning) models. Recently, several Explainable Artificial Intelligence (XAI) techniques (e.g., SHAP, LIME) have been introduced that can be leveraged to interpret the performances of these models. However, users often face challenges when they attempt to employ XAI techniques and post questions at Stack Overflow to resolve these challenges. Aiming to introduce automated support, we first conduct an exploratory study to gather challenge insights and produce a catalog of these challenges. Several studies have looked into the problems that come with XAI, such as disagreement problems, XAI for cybersecurity, privacy and data fusion, ethical and legal issues that make people not trust XAI, problems with putting it to use in clinical settings, and so on. However, exploring the usage and integration challenges of XAI techniques is still an unmet attempt. In this study, we make two contributions. First, we manually investigated 556 questions of Stack Overflow that discussed XAI-related challenges and spent 40 person-hours. Our careful investigation produced a catalog of six challenges (e.g., incompatible with multiple AI models). Second, we conducted an empirical analysis to see the severity of each challenge. In particular, we determine the correlation between challenge type and answer metadata such as acceptable answers, delay between question submission, and getting acceptable answers and getting answers or not. Our study findings might (1) help to enhance the accessibility and usability of XAI and (2) act as the initial benchmark that can inspire future research.

## CCS CONCEPTS

• **StackOverflow → XAI Techniques**.

## KEYWORDS

Explainability Challenges, Stack Overflow, LIME, SHAP, Software Maintenance

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## 1 INTRODUCTION

The field of Explainable Artificial Intelligence (XAI) has become a significant domain of study and advancement aimed at improving the clarity and comprehensibility of machine learning models. The rising complexity of machine learning algorithms necessitates the development of tools. It aims to elucidate their decision-making processes, particularly in domains with significant consequences, such as healthcare [1], finance [2], and autonomous systems [3]. LIME (Local Interpretable Model-agnostic Explanations) [4] and SHAP (SHapley Additive exPlanations) [5] are two extensively employed strategies in the field of Explainable Artificial Intelligence (XAI). These methods are specifically developed to provide interpretability and understanding of the predictions made by intricate models. Even with their widespread popularity, the successful execution of these methodologies presents obstacles for software engineers.

It is essential to comprehend the complexities of XAI approaches and the challenges developers face when implementing them if we hope to see their widespread adoption. By analyzing the questions asked on Stack Overflow, we want to learn more about the reasons behind developers' search for solutions. The combined expertise of developers on this platform offers priceless insights, whether tackling installation problems, Library issues, Value errors, visualization problems, compatibility issues, and so on. The motivation behind this investigation is the aspiration to narrow the existing knowledge gap, provide resolutions to prevalent issues, and enable a smoother incorporation of XAI techniques into real-world implementations.

This study examines the complex range of challenges software developers face while applying XAI methodology, with a specific focus on using LIME and SHAP techniques. Stack Overflow, a well-recognized forum for developer discussions and problem-solving, functions as an excellent repository of practical challenges and enquiries about the real-world implementation of these methodologies [6–8]. Many software developers engage monthly with Stack Overflow (SO) to address their programming-related issues [9]. Approximately 7,000 enquiries are posted daily on Stack Overflow (SO). Within the set of queries, a significant proportion pertains to problems at the code level, such as mistakes and unexpected behaviour (e.g., [7]). Frequently, these enquiries consist of troublesome code parts and descriptions of the programming issues. This study aims to analyze questions and debates on Stack Overflow to determine the prevailing issues developers typically find in Explainable Artificial Intelligence (XAI).

Furthermore, the primary objective of this research is to provide a comprehensive understanding of the specific concepts associated with Explainable Artificial Intelligence (XAI) that developers perceive as particularly intricate. To effectively use XAI approaches, it is crucial to have a comprehensive understanding of these conceptual challenges [10–14]. This understanding is necessary for the customization of instructional resources and tools that effectively address the concerns faced by developers. Our investigation produces a catalog of real-world challenges (see Table 1) that developers face with XAI techniques. The catalog shows the more frequent challenges of using LIME and SHAP. Thus, it is still being determined how the developers perceive these challenges. Understanding the developers' perspective is essential to introduce efficient tool support to promote user-friendly XAI techniques.

**Table 1**
**Challenges of XAI techniques**

| **Identified Challenges** |
|---|
| Incompatible to Multiple Models |
| XAI Model Installation Issues |
| Visualization Discrepancy |
| XAI Model Integration Issues |
| Performance Deviation of XAI from Classifiers |
| Miscellaneous |

The objective of this enquiry is to gain a comprehensive understanding of the current state of affairs by examining the challenges, theoretical intricacies, and unanswered questions about techniques in Explainable Artificial Intelligence (XAI). Gathering this knowledge is of utmost importance in facilitating the development of a landscape for Explainable Artificial Intelligence (XAI) that is both accessible and hospitable for developers. Ultimately, this will contribute to the responsible and ethical utilization of machine learning models across various applications.

## 2 RELATED WORK

Stack Overflow is a helpful repository where developers get together to explore the complexities of implementing and utilizing Explainable Artificial Intelligence (XAI) approaches such as LIME and SHAP. The platform is characterized by a high level of activity, reflecting the efforts of developers to comprehend the underlying mechanisms, overcome installation challenges, address compatibility problems, and unravel the complexities associated with visualizing these explainable artificial intelligence (XAI) approaches [8]. In software development, the queries posted on Stack Overflow serve as a dynamic platform that captures the ongoing challenges, uncertainties, and persistent obstacles developers encounter as they navigate the intricacies of LIME and SHAP methodologies [9]. The diverse range of investigations encompasses the continuing pursuit to overcome gaps in understanding and tackle practical obstacles in utilizing Explainable Artificial Intelligence (XAI) in machine learning models. This highlights the platform's significance as a guiding light for practical knowledge and resolving issues in transparent AI.

Many research studies have been conducted to examine the problems related to usability, such as parsability and compilability, as well as executability and reproducibility of code segments that are shared on crowd-sourced developer forums like GitHub and Stack Overflow. Various sources have referenced these studies [15–21] This study initially examines practitioners' viewpoints regarding the obstacles associated with LIME and SHAP technique issues reported in Stack Overflow (SO) questions. We also explore the influence of these challenges on the ability to provide answers to such questions. In their study, Yang et al. [20] analyzed the usability of around 914,000 Java code segments. These code segments were collected from the acceptable responses found on Stack Overflow. The authors highlight various difficulties in the interpretability of their code, such as syntax errors and issues related to the compatibility of different data types throughout the compilation process. The authors utilize automated tools, specifically Eclipse JDT and ASTParser, to analyze and compile code segments. They identify and document the obstacles that hinder the parsing and compilation process. Nevertheless, the authors must address the complexities of the repeatability issue. The executability of Python code on the GitHub Gist system is investigated by Horton and Parnin [16]. The authors document the various categories of execution failures that are encountered during the execution of Python gists, including import errors, syntax errors, and indentation errors. Nevertheless, successfully executing a code segment does not necessarily ensure the replicability of a problem stated in a Stack Overflow query.

Giving someone with a defensible set of model results is the first step in explaining the ML model. For example, the rationale for employing a black box model elucidates the importance of the decision undertaken. In their study, Montavon et al. [22] provide various approaches to elucidating individual outcomes derived from deep neural networks. The authors primarily focus on the theoretical aspects that render these interpretations practically significant. There has been a surge of studies on explainability methods within the machine learning community. Typically, these strategies can be categorized into two approaches: the utilization of "glass-box" machine learning models, which are inherently interpretable (e.g., Generalized Additive Models), and the application of post-hoc explanation methods, which aim to enhance the interpretability of "black-box" models (e.g., Local Interpretable Model-Agnostic Explanations (LIME) by Ribeiro et al. [4] and Shapley Additive exPlanations (SHAP) by Lundberg et al. [5].

Rudin et al. [23] contend that applying post hoc explanation methods for machine learning models in high-stakes domains may not reliably address the behaviour of these models. According to Doshi-Velez et al. [24], it is suggested that explanations about a particular forecast should include both a justification and a depiction of the dynamic interaction employed by the model. In their study, Lipton et al. [25] provide a comprehensive examination of many approaches to assess interpretability, such as implacability, and discuss numerous aims that can be achieved through interpretability.

Jiarpakdee and colleagues [26] discuss the difficulties associated with comprehending and interpreting the predictions produced by software defect models. The study conducted by Roy et al. [27] focuses on characterizing disputes among different post-hoc explanations of defect predictions. This research provides significant insights into the landscape of explainable artificial intelligence (XAI) in software engineering. This study holds practical significance in software engineering as it aims to enhance the transparency and comprehensibility of defect prediction models. These improvements are crucial for making informed software development and quality assurance decisions. In contrast to many articles on explainable artificial intelligence, the article authored by Dovsilovi'c et al. [28] focuses on providing elucidations and interpretations of unsupervised machine learning techniques. The report analyzes the coordinated (transparency-based) and post hoc methods and discusses Explainable Artificial Intelligence (XAI).

Several studies [10, 12, 13] emphasize the intricate nature of the trade-off between the interpretability of models and their performance. This observation brings attention to the widespread problem of black-box models within deep learning that impedes the comprehension of decision-making mechanisms. The authors also explore the challenges associated with adequately communicating complex AI outputs to individuals who lack expertise in the field, highlighting the importance of enhancing Human-Computer Interaction (HCI). Furthermore, the study addresses the issue of the need for standardized evaluation metrics for explainable artificial intelligence (XAI) methods, which poses a challenge in comparing and evaluating various methodologies. Ultimately, this study acknowledges the issue of domain specificity, suggesting that XAI methodologies may necessitate customized techniques to accommodate multiple application domains.

The study [11, 29–31] provides a thorough analysis of the many obstacles encountered in implementing Explainable AI (XAI) within clinical decision support systems that rely on machine learning algorithms. The paper underscores the difficulties associated with achieving model interpretability in healthcare contexts, emphasizing the intrinsic intricacy of medical data and the imperative for AI-driven suggestions that are understandable and reliable. This study explores the challenges associated with integrating explainable artificial intelligence (XAI) techniques into established clinical workflows, focusing on assuring their compatibility with the decision-making practises of medical professionals. Additionally, the study highlights the significance of acknowledging ethical considerations, including safeguarding patient confidentiality and mitigating bias, particularly in implementing artificial intelligence (AI) systems within the healthcare domain. Furthermore, it elucidates the difficulty of striking a balance between the intricacy of models and their interpretability, underscoring the imperative of developing models that possess precision and transparency to facilitate clinical decision-making. However, we plan to determine which problems are actually facing the software developers for solving or implementing XAI techniques in real-world scenarios. If we can find out the real problem that is happening, it would be easier to build a concrete system. And that time, we can propose a new tool or update the existing tools that will not encounter any problems.

## 3 STUDY DESIGN

This study aims to investigate the developer's perspective on the challenges of XAI techniques. The objective of this study is to contribute meaningful insights that inform future research directions, instructional curricula, and tool development in the field of Explainable Artificial Intelligence (XAI). This will be achieved by examining the areas of interest among developers and finding enduring gaps in knowledge. In pursuit of this objective, our work is guided by three research enquiries and presents three contributions in this manuscript, as delineated below.

**RQ1. What difficulties do developers see underlying the XAI approach issues that are highlighted in enquiries on Stack Overflow?**
When developers explore XAI methodologies, they frequently encounter complex issues brought to attention through queries on Stack Overflow. The challenges encompass a range of areas, including obstacles related to the execution of tasks, such as installing, integrating, and configuring the system within pre-existing frameworks. Utilizing approaches such as LIME or SHAP introduces challenges in visualizing and interpreting the generated explanations. Consequently, developing efficient strategies for effectively presenting and comprehending these explanations is imperative. The obstacles are further compounded by compatibility issues arising from using disparate frameworks or software versions and performance considerations. Prominent challenges arise in comprehending the theoretical underpinnings, managing faults, guaranteeing scalability, and upholding security and reliability. The aforementioned array of issues highlights the wide variety of obstacles developers encounter while utilizing XAI approaches in their applications.

**RQ2. Which types of XAI challenges are more prevalent than others?**
Within the domain of Explainable Artificial Intelligence (XAI), various issues have been identified through extensive debates on sites like Stack Overflow. Among these challenges, certain ones are considered more important and urgent than others. The main category of challenges in this context mainly comprises implementation hurdles. These barriers pertain to many aspects, such as the installation procedures, setup configurations, and the smooth integration of XAI techniques into pre-existing systems or frameworks. Furthermore, the issues about interpretability and visualization, including understanding the theoretical foundations and proficiently communicating the results, have become prominent subjects of discussion. In addition to these factors, there is significant focus and discussion surrounding concerns related to compatibility across various platforms, versions, or frameworks, as well as the necessity for performance optimization. The problems above frequently precede conversations and investigations, underscoring their importance in implementing and accepting XAI methodologies.

**RQ3. How does the severity level of XAI challenges impact the adoption rate of XAI techniques?**
The prevailing concerns around explainable artificial intelligence (XAI) techniques on platforms such as Stack Overflow frequently highlight an ongoing necessity for additional examination and resolution. Despite extensive conversations and contributions, many of these difficulties persist without explanation or complete mitigation. Users commonly post enquiries to obtain a more comprehensive understanding, explore other methodologies, or receive improved answers, demonstrating a continuous pursuit for enhanced clarity and more efficient resolutions. This observation indicates that numerous issues in explainable artificial intelligence (XAI) are still being actively investigated, underscoring the intricate nature of these challenges and the necessity for continued improvement in XAI methodologies.

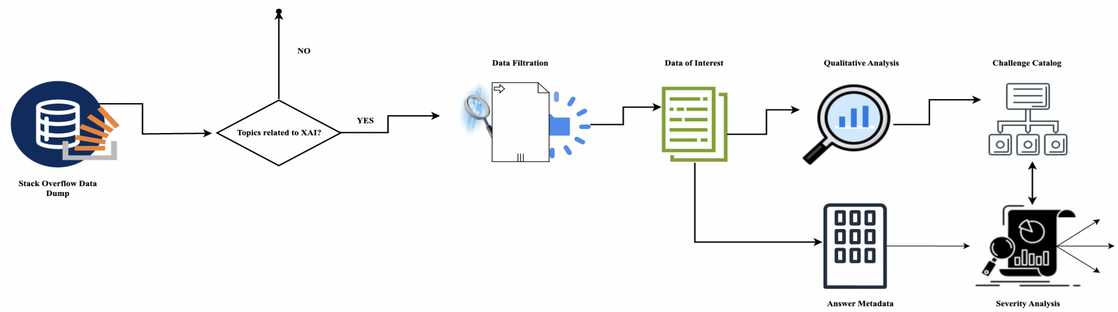



**Figure 1: Schematic diagram of our exploratory study**

To the extent of our current understanding, there is a need for more research to investigate the practical challenges encountered by application developers in the development of explainability applications. The present analysis, however, emphasizes Stack Overflow. Further investigation is warranted for this critical line of enquiry for two primary reasons. Firstly, a lack of comprehension regarding the requirements and obstacles encountered by developers may lead researchers to concentrate on addressing issues that, while intriguing, are only experienced by a limited number of developers in real-world scenarios. Secondly, the presence of conceptually flawed perspectives among researchers may catalyze educators to design more advanced and up-to-date curricula.

# 4 RESEARCH METHODOLOGY:

The schematic diagram (see Figure 1) shows our investigation process. The study starts with extensive data collection from Stack Overflow, focusing on questions related to XAI techniques such as SHAP and LIME. A comprehensive dataset is gathered, filtering for questions, answers, and metadata, specifically discussing these techniques. The filtration process involves using relevant tags, keywords, or specific categories to extract pertinent discussions related to XAI. Once the data of interest is collected, it is organized and structured for analysis. Qualitative analysis involves categorizing and understanding the nature of challenges faced by developers concerning XAI techniques. It includes examining the question content, answer metadata, the issues' severity, and the discussions' depth. Challenge categories are identified based on users' recurring themes or problems in their XAI implementations. All the processes have been described clearly in the subsection 4.1, 4.2, 4.3, and 4.4.

## 4.1 Data Collection

The dataset selection employed in this study adopts a mixed-methods approach, encompassing quantitative and qualitative data collection. By utilizing the StackExchange website, users can execute queries within the most current StackOverflow database. The database was utilized to extract questions, answers, tags, and additional metadata. The data presented in this study is derived from using eXplainable Artificial Intelligence (XAI) approaches. Upon conducting an initial search, it is evident that the topic of "XAI" encompasses a limited number of 33 queries. A deliberate decision was made to meticulously choose and examine a total of 556 questions, representing approximately 1% of the entire XAI-related questions. To accurately ascertain this curated compilation, we initially searched for enquiries with at least one keyword connected to explainable artificial intelligence (XAI) inside their associated tags. The decision to not filter the body or title of the questions was based on two primary reasons. Firstly, it was observed that every question in the dataset was associated with at least one tag. Secondly, it was anticipated that related questions would likely employ a self-explanatory or easily understood tag. In our study, we used many XAI keywords, including "LIME," "SHAP," "Breakdown," "PyExplainer," "Saliency Map," "anchors," "TimeLime," "LOCO," and "GradCAM." We received 565 enquiries about the topics of LIME and SHAP. Surprisingly, no additional question relevant to methods was discovered. A preliminary enquiry into the topic of "Explainable Artificial Intelligence (XAI)" was conducted, followed by subsequent investigations into the methodologies known as "Local Interpretable Model-Agnostic Explanations (LIME)" and "SHapley Additive exPlanations (SHAP)." As of the present date, 16 November 2023, a cumulative count of 598 enquiries has been recorded. Several duplicate and irrelevant questions have been eliminated. Ultimately, out of the 598 questions that include at least one term from the abovementioned keywords, we filtered and chose 556 questions for analysis.

## 4.2 Sentiment Analysis

Sentiment analysis techniques can be employed to estimate developers' sentiment towards different XAI techniques. This could involve determining the positivity or negativity of discussions surrounding LIME, SHAP, and other XAI methods. For example:

- Positive Sentiment: "I found SHAP explanations incredibly insightful and easy to implement!"
- Neutral Sentiment: "Has anyone encountered issues with LIME in Python?"
- Negative Sentiment: "LIME's documentation lacks clarity and makes it hard for beginners to understand."

## 4.3 Trend Analysis

Trend analysis entails the examination of patterns and changes over time in talks. This encompasses the process of recognizing emergent subjects, shifts in interests, or persistent challenges encountered by developers across a period. For example:

- There have been increased questions related to SHAP and LIME adoption over the past year.
- A sudden surge in queries regarding specific problems with LIME post a recent update or release.

### 4.4 Quantitative and Qualitative Analysis

The comprehensive examination of the challenges, questions, and overall impact of XAI techniques on Stack Overflow can be achieved by employing a combination of quantitative metrics, such as the frequency of topics and engagement metrics, and qualitative insights, which provide a contextual understanding of the discussions. For example:

- Quantitative: Counting the number of questions tagged with 'SHAP' or 'LIME' to gauge their popularity.
- Qualitative: Reviewing specific questions or answers to understand in-depth issues developers face, such as confusion about implementation or challenges in interpreting results.

## 5 DISCUSSION

This section commences with an introduction to the problem of XAI techniques and the obstacles that impede its achievement. This section also describes the severity of each challenge (see Table 1).

***A. Incompatibility to Multiple Models:***

The issue of "Incompatibility to Multiple Models" is recognized as a substantial obstacle within the eXplainable Artificial Intelligence (XAI), comprising 16.01% (see Table 2) of the many challenges encountered. This matter holds great importance for developers utilizing platforms such as Stack Overflow. This challenge encompasses the intricacies of using explainable artificial intelligence (XAI) approaches across diverse machine learning models, such as LIME or SHAP [32, 33]. The issue emerges due to the limitations of these methodologies in effectively adjusting and delivering coherent explanations across a wide range of model designs and data types. The significance of this difficulty stems from the observation that although these techniques may accurately interpret the predictions of a particular model, their effectiveness may greatly diminish when used in different models, leading to explanations that are inconsistent or lacking in reliability. This inconsistency hinders the widespread deployment of XAI techniques and reduces their efficacy in promoting model transparency and interoperability [34]. The challenge of being "Incompatible with Multiple Models" significantly impedes the uniform application of XAI techniques across diverse machine learning models, demanding tailored solutions and a deeper understanding of model-specific intricacies to ensure consistent and reliable interpretability.

***B. XAI Model Installation Issues:***

The impact of installation issues related to XAI models hinders developers' efforts to include these models into their workflow smoothly. This obstacle hinders the effective implementation of eXplainable Artificial Intelligence (XAI) methods, which play a crucial role in improving the interpretability and transparency of models. As a result, developers confront obstacles in comprehending and articulating machine learning models proficiently, primarily attributable to the difficulties faced throughout the installation process [35–38]. Consequently, adopting XAI solutions hinders machine

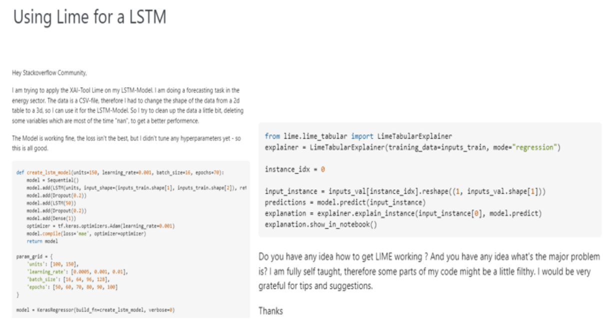



**Figure 2: An example of a question on Stack overflow related to Incompatible for multiple models [32]**

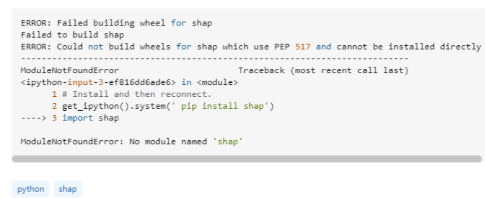



**Figure 3: An example of a question on Stack overflow related to XAI Model Installation Issues [35]**

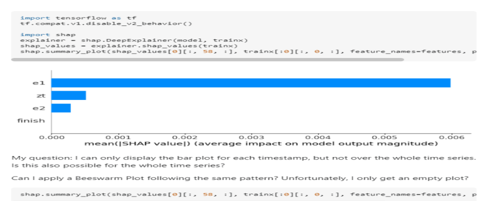



**Figure 4: An example of a question on Stack overflow related to XAI Visualization Discrepancy [39]**

learning models' overall efficacy and transparency in various applications or systems. The installation issues related to XAI models provide a substantial obstacle for developers, constituting 27.51% of the encountered obstacles. The problem is commonly noticed in configuration failures or challenges faced during the installation process of eXplainable Artificial Intelligence (XAI) models. This observation is derived from many queries on platforms like Stack Overflow. The issues frequently pertain to the intricacies associated with establishing or incorporating explainable artificial intelligence (XAI) methodologies, such as LIME or SHAP, inside pre-existing frameworks or contexts. Software developers frequently encounter challenges related to disparities in software versions or inadequate documentation, resulting in installation failures or mistakes during the setup process [36–38]. This obstacle greatly hinders the smooth implementation of XAI approaches, impeding developers' endeavours to utilize these tools to boost model interpretability and transparency.

***C. Visualization Discrepancy:***

The significance of disparities in visualization within eXplainable Artificial Intelligence (XAI) methods holds considerable implications for developers. These challenges hinder the successful interpretation and comprehension of model explanations generated by XAI tools like LIME and SHAP. Challenges in plotting figures [40], discrepancies in visual representations, and difficulty grasping feature importance from graphs create a bottleneck in developers' endeavours to extract insights and make educated decisions using model explanations [39, 41]. As a result, the lack of proficiency in visualizing and comprehending these explanations reduces the clarity and interpretability of machine learning models, hence limiting their potential influence and practicality in real-world situations. The importance of the visualization effect in LIME and SHAP figures is crucial for improving the interpretability of machine learning models and tidymodels [42]. The presence of discrepancies or inconsistencies in the plots, which present varying outcomes for a given explanation, substantially affects the credibility and dependability of the explanations offered by eXplainable AI (XAI) methods. Developers utilize visualizations as a means to appreciate the significance of features and gain an understanding of the behaviour exhibited by the model. The presence of inaccurate or inconsistent data can give rise to misinterpretations, leading to faulty decision-making, diminished confidence in the model's explanations, and the possibility of deploying erroneous models in essential fields [43]. These inconsistencies hinder the clarity and practicality of eXplainable Artificial Intelligence (XAI) techniques, hence obstructing their practical use in real-world scenarios.

Consider a scenario where a data scientist analyzes a time series model predicting stock prices. They use SHAP to understand how different features contribute to these predictions over time. The data scientist generates SHAP summary plots for the time series model in this analysis [39]. The SHAP summary plot showcases the feature importance for various predictors over different periods. For instance, the plot highlights that during market volatility, features like trading volume, news sentiment, and historical stock performance are critical in influencing stock price predictions. The SHAP values for time series illustrate how certain features' impact on predictions fluctuates over different time intervals. For instance, before significant market events, news sentiment might have a more substantial effect, while technical indicators might be more influential during regular trading periods. However, when interpreting these SHAP plots for time series, the data scientist encounters a challenge. The plots might reveal fluctuations or sudden changes in feature importance, making it challenging to draw consistent conclusions about the specific influence of each feature across time intervals. This complication can make it more challenging to deliver concrete insights to stakeholders or necessitate extra investigation to identify the underlying causes of these changes.

In summary, while SHAP plots for time series provide valuable insights into feature importance variations over time, interpreting these plots might pose challenges due to the dynamism and changing impact of features across different periods in the time series data.

### D. XAI Model Integration Issues:

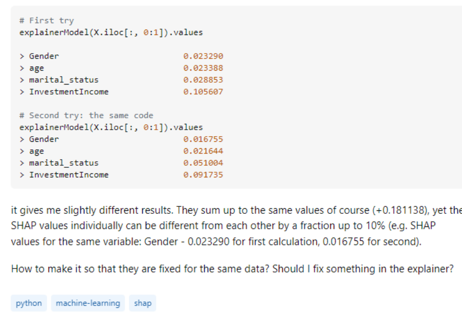

```
--> 127         return cv2.inpaint(
    128             x.reshape(self.input_shape).astype(np.uint8),
    129             reshaped_mask,

error: OpenCV(4.7.0) /io/opencv/modules/photo/src/inpaint.cpp:767: error: (-210:Unsupporte
```

Any suggestion/comments is highly appreciated. i spent lot of time on it without any success even CHATGPT was not very helpful

transfer-learning image-classification shap xai cifar100

**Figure 5: An example of a question on Stack overflow related to XAI Model Integration Issues [46]**


```
# First try
explainerModel(X.iloc[:, 0:1]).values

> Gender                        0.023290
> age                           0.023388
> marital_status                0.028853
> InvestmentIncome              0.105607

# Second try: the same code
explainerModel(X.iloc[:, 0:1]).values
> Gender                        0.016755
> age                           0.021644
> marital_status                0.051004
> InvestmentIncome              0.091735
```

it gives me slightly different results. They sum up to the same values of course (+0.181138), yet the SHAP values individually can be different from each other by a fraction up to 10% (e.g. SHAP values for the same variable: Gender - 0.023290 for first calculation, 0.016755 for second).

How to make it so that they are fixed for the same data? Should I fix something in the explainer?

python machine-learning shap

**Figure 6: An example of a question on Stack overflow related to Performance Deviation of XAI from Classifiers [47]**

XAI Model Integration Issues encompass the challenges of seamlessly incorporating eXplainable Artificial Intelligence (XAI) techniques like LIME and SHAP into complex machine learning architectures. Failure to properly integrate these XAI methods with intricate models, such as ensemble models or deeply interconnected neural networks [44], can hinder the extraction of accurate and meaningful explanations for model predictions. This inability to effectively interpret [45] and explain model decisions may result in a lack of transparency, reduced trust in the model's outcomes, and limited adoption of sophisticated machine learning systems in critical domains like healthcare, finance, or autonomous techniques. Consequently, improper integration impedes the broader goal of establishing trustworthy, interpretable AI systems in real-world applications.

SHAP works for image classification without Transfer learning, but the user got this error when applying SHAP to TL-based image classification. The user posted the question on stack overflow named "How to use SHAP for VGG16 for image classification through Transfer Learning" [46]. Figure 5 shows the code followed by the error:

### E. Performance Deviation of XAI from Classifiers

The performance deviation of eXplainable Artificial Intelligence (XAI) techniques, such as LIME and SHAP, from classifiers pertains to the reported inconsistencies in their performance when interpreting classifiers, particularly in the context of software defect prediction scenarios. For example, let us suppose a scenario in which a software development team is utilising a machine learning classifier to forecast software problems by analysing many features. The classifier has strong performance metrics, yielding precise predictions. Nevertheless, when utilising explainable artificial intelligence (XAI) methods such as LIME and SHAP to understand the predictions

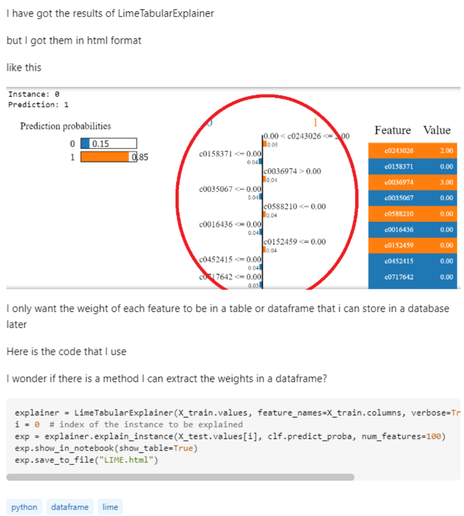



**Figure 7: An example of a question on Stack overflow related to miscellaneous problems about how to store LIME results to a table instead of show_in_notebook or save_to_file [48]**

made by the model, a discernible disparity becomes apparent in the explanations supplied. The LIME method has the potential to identify specific features as influential, even if the classifier did not heavily depend on them. This might result in a divergence between the explanation provided by LIME and the actual decision-making process of the classifier. In a similar vein, the SHAP method, which aims to allocate importance to features, has the potential to assign varying values that deviate substantially from the internal mechanism of the classifier. The discrepancy in performance seen might be a source of confusion for developers, since the explanations generated by XAI techniques may not accurately correspond to the classifier's decision boundaries. This misalignment has the potential to hinder the trust and acceptance of these techniques in models used for predicting software defects.

***F. Miscellaneous:***

In addition to the previously discussed challenges, software developers encounter various other issues when implementing LIME and SHAP techniques, as evident from their queries on StackOverflow:

- Data Preprocessing and Feature Engineering Challenges: Developers seek guidance on preprocessing techniques and feature engineering methods compatible with LIME and SHAP, especially when dealing with categorical variables, text data, or high-dimensional features.
- Incorporating Domain Knowledge: Users often struggle to integrate domain-specific knowledge into LIME and SHAP explanations effectively. They seek advice on how to merge external domain expertise with model interpretations to enhance the relevance and accuracy of explanations.
- Robustness and Stability of Explanations: Concerns arise regarding the stability and robustness of explanations provided by LIME and SHAP. Developers encounter scenarios where small changes in data or models lead to significantly different explanations, prompting them to inquire about more stable and reliable methodologies.
- Interpretability of Complex Models: Implementing LIME and SHAP with complex models, including deep learning architectures or ensemble methods, poses challenges in achieving comprehensible and interpretable explanations, leading users to explore alternatives or workarounds [49].
- Scalability and Memory Efficiency: Users express concerns about LIME and SHAP's scalability and memory efficiency, mainly when dealing with large-scale datasets or models. They seek optimizations and techniques to improve computational efficiency without compromising accuracy.
- Privacy and Ethical Concerns: Addressing privacy issues related to sensitive data when utilizing LIME and SHAP explanations remains a concern. Developers inquire about privacy-preserving methodologies and ethical considerations when interpreting models, especially in regulated domains.

These diverse challenges illustrate the multifaceted nature of issues faced by developers when implementing LIME and SHAP techniques. Overcoming these challenges requires holistic solutions that cater to the complexities of real-world data and models while ensuring robust, interpretable, and efficient explanations.

# 6 RESULT ANALYSIS

**[RQ1.] What difficulties do developers see underlying the XAI approach issues that are highlighted in enquiries on Stack Overflow?**

Questions posted on Stack Overflow shed light on the complex issues that software developers confront when working with eXplainable Artificial Intelligence (XAI) methods, as shown in Figure 8. These include complicated integration difficulties such as version discrepancies and compatibility issues, which prevent the smooth incorporation of XAI tools such as LIME and SHAP into preexisting machine learning workflows. In particular, models constructed using deep learning or ensemble approaches might be challenging to interpret due to their opaque nature. Difficulty understanding feature importance and model predictions is compounded by inconsistencies in visualization, especially between SHAP and LIME explanations. There are also questions about the performance scalability of XAI approaches, mainly when dealing with large datasets and complex models while also guaranteeing domain generalizability and ethical issues. These varied problems highlight the need for all-encompassing answers that consider model justifications' technical, interpretability, and ethical aspects.

Developers encounter several challenges (see Table 1) when dealing with eXplainable Artificial Intelligence (XAI) techniques, as reflected in their inquiries on Stack Overflow:

- **Domain compatibility:** Implementing XAI techniques across diverse domains presents challenges in adapting these methods to domain-specific data and understanding. Developers often seek insights into effectively incorporating domain knowledge into the interpretation process.
- **Installation and Implementation Issues:** Developers face hurdles integrating XAI techniques like LIME and

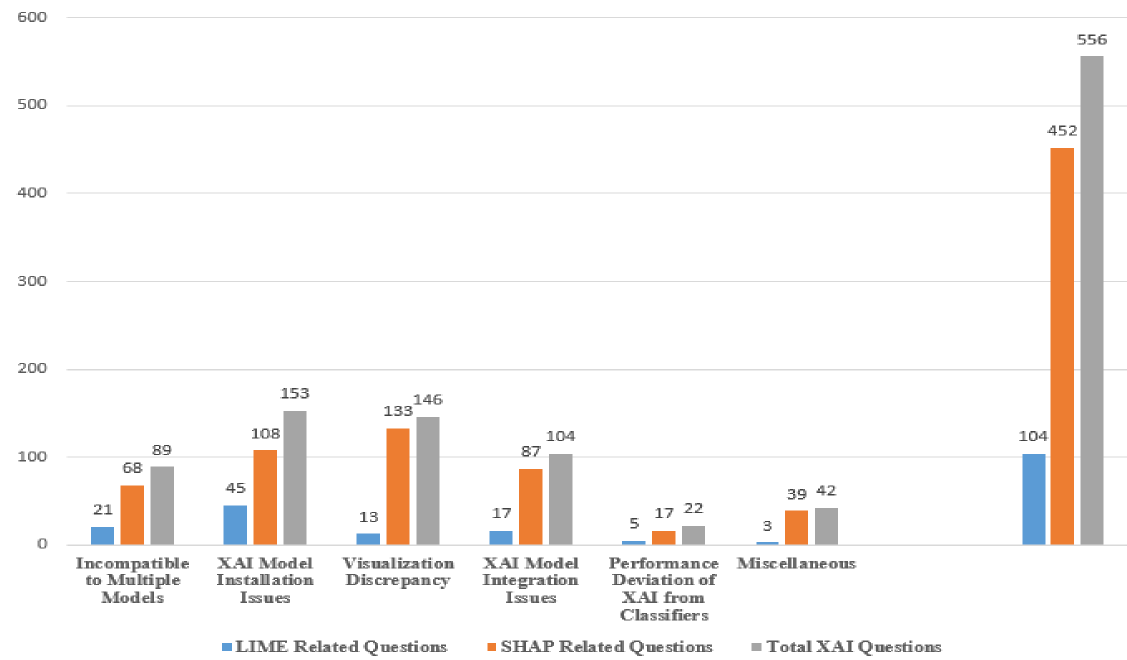



**Figure 8: XAI approach issues on Stack Overflow**

SHAP into their existing machine-learning pipelines. Issues arise during the implementation phase, such as compatibility problems, version mismatches, and challenges in integrating these techniques seamlessly with various machine learning frameworks.
- **Visualization and Explanation Discrepancies:** Users encounter discrepancies and difficulties in visualizing and understanding the explanations provided by XAI techniques. They struggle with differences between SHAP and LIME explanations, especially when interpreting feature importance and model predictions.
- **XAI Model Integration Complexity:** Understanding and interpreting complex machine learning models remains a significant challenge. Developers seek guidance on effectively utilizing XAI techniques to integrate multiple models, especially those involving deep learning or ensemble methods, which often lack transparency.
- **Performance Deviation and Scalability Concerns:** XAI techniques sometimes face limitations in handling large datasets and complex models efficiently. Developers inquire about optimizing the performance and scalability of these methods without compromising accuracy or interpretability.
- **Miscellaneous:** Addressing ethical concerns, trustworthiness, consistent output explanation, application ambiguity, exception handling, and so on are related to the interpretation and explanation of models, especially in regulated domains like healthcare or finance and the software industry is another challenge. Developers seek guidance on maintaining privacy and ethical standards while interpreting models using XAI techniques.

These challenges highlight the multifaceted nature of hurdles developers face when implementing XAI techniques, emphasizing the need for comprehensive solutions that address the technical, interpretability, and ethical aspects of model explanations.

**[RQ2.]Which types of XAI challenges are more prevalent than others?**

Gaining a comprehensive understanding of the predominant obstacles that software developers face when implementing eXplainable Artificial Intelligence (XAI) approaches is crucial for the progress and practical utilization of such methods. Examining Stack Overflow data uncovers discernible obstacles that exhibit varied levels of significance.

Table 2
Challenges ratio of XAI techniques

| Identified Reason | Percentage |
|---|---|
| Incompatible to Multiple Models | 16.01% |
| XAI Model Installation Issues | 27.51% |
| Visualization Discrepancy | 26.26% |
| XAI Model Integration Issues | 18.71% |
| Performance Deviation of XAI from Classifiers | 3.96% |
| Miscellaneous | 7.55% |

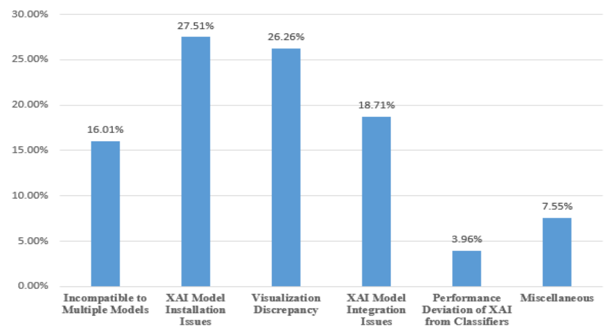



**Figure 9: Ratio of each challenge**

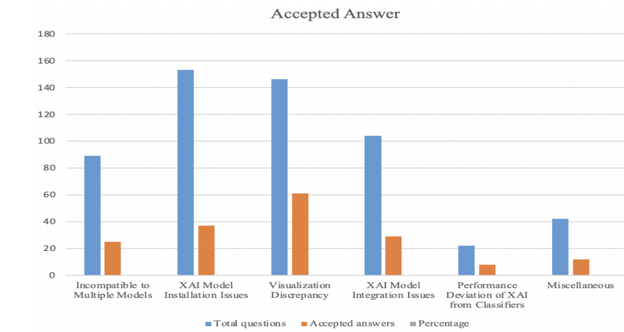



**Figure 10: Accepted answer**

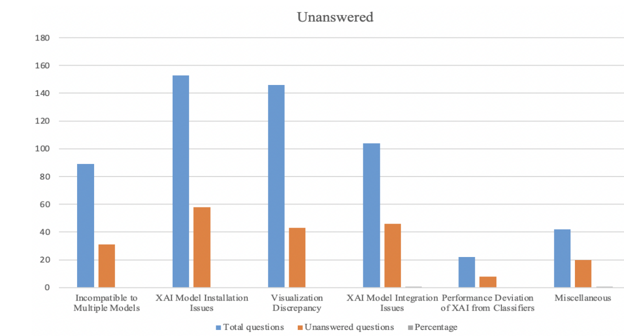



**Figure 11: Unanswered questions**

Figure 9 and Table 2 show the predominance of obstacles in Explainable Artificial Intelligence (XAI), as indicated by the percentages derived from Stack Overflow data, underscores the prominence of specific concerns over others in real-world applications. The field's predominant concern is installation difficulties, accounting for around 27.51% of the reported issues. These challenges involve problems encountered when installing, setting, and using XAI frameworks, libraries, or tools across diverse software systems. The presence of visualization discrepancies is at a significant rate of 26.26%, suggesting substantial challenges in comprehending and interpreting the visual outputs produced by explainable artificial intelligence (XAI) systems. The challenges associated with integration, accounting for 18.71% of the overall concerns, about the intricate nature of seamlessly embedding eXplainable Artificial Intelligence (XAI) techniques into pre-existing models or data pipelines. Challenges related to compatibility across various models account for 16.01% of the total, suggesting that applying Explainable Artificial Intelligence (XAI) methodologies to diverse machine learning architectures is accompanied by complexities. Miscellaneous difficulties comprise a range of less prevalent disorders, constituting 7.55%. Finally, a smaller proportion of 3.96% can be attributable to performance deviations of explainable artificial intelligence (XAI) from classifiers. This indicates situations where XAI techniques exhibit deviations from the anticipated performance in data classification. The above rates highlight the significance and range of difficulties developers encounter while implementing XAI approaches.

**[RQ3.]How does the severity level of XAI challenges impact the adoption rate of XAI techniques?**

The existence of XAI problems on platforms such as Stack Overflow indicates ongoing topics requiring additional investigation. Even with the concerted endeavours of the community, a significant multitude of challenges endure with the implementation of complete solutions. Recurring challenges, such as the installation issues of XAI models and discrepancies in visualization, persistently hinder progress, indicating an absence of conclusive resolutions. Likewise, the investigation into XAI Model Integration and Compatibility with Multiple Models continues to be a topic of interest, underscoring the intricate nature of these multidimensional concerns. The persistent pursuit of resolutions highlights the necessity for an ongoing investigation, cooperative efforts, and inventive approaches to effectively address the remaining challenges and promote the practical implementation of XAI technologies.

Figure 10, 11, and 12 clearly depicts the severity of XAI challenges. The statistics portray a spectrum of severity challenges developers encounter in the realm of eXplainable Artificial Intelligence (XAI) techniques, as gleaned from Stack Overflow. Of particular note, problems with "Visualisation Discrepancy" become the most common problem, making up 41.80% of accepted answers and 29.50% of unanswered questions. This highlights a critical hurdle in interpreting and comprehending XAI visualizations, potentially leading to misinterpretations or misjudgments in model understanding. "XAI Model Integration Issues" come close behind, affecting 27.90% of answered questions and an alarming 44.20% of unanswered concerns, showing that integrating XAI into different systems can be very difficult. "XAI Model Installation Issues" and "Incompatible to Multiple Models" have low acceptance rates (24.20% and 28.10%, respectively). Still, they have many unanswered questions (37.90% and 34.80%), which shows that it is still hard to implement and adapt XAI models across different frameworks. "Miscellaneous" issues and "Performance Deviation of XAI from Classifiers" also have moderate to high acceptance rates but many unanswered questions, which means there is still a lot of uncertainty and problems in these areas that need to be solved. Overall, these statistics underscore the pressing need for more comprehensive and accessible solutions in XAI techniques to address these issues encountered by developers on Stack Overflow.

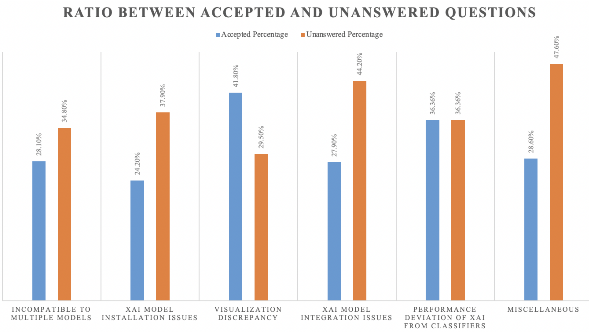



**Figure 12: Ratio between answered and unanswered questions**

# 7 IMPLICATION

The actual deployment of Explainable Artificial Intelligence (XAI) techniques encounters various problems as they continue to advance. The present study utilizes the dynamic nature of Stack Overflow discussions to extract significant insights essential for influencing the trajectory of Explainable Artificial Intelligence (XAI) adoption. This study endeavours to analyze and integrate the extensive information and experiences developers contributed to comprehend the complexities associated with implementing Explainable Artificial Intelligence (XAI). Additionally, it seeks to anticipate the potential ramifications of the widespread incorporation of XAI into practical applications.

The high frequency of enquiries on Stack Overflow exemplifies the community-driven nature of problem-solving in the XAI sector. Developers engage in joint problem-solving efforts, actively contributing to a shared store of knowledge. This highlights the significance of cultivating community involvement and forums for exchanging knowledge to ensure continuous support.

The presence of enquiries about core concepts suggests the existence of substantial disparities in education regarding the comprehension of XAI approaches. Identifying and resolving these deficiencies offers potential for educational endeavours to equip developers with the requisite competencies and to utilize XAI effectively.

Developers often seek assistance with installation, compatibility, and visualization concerns who need user-friendly tools and documentation. This observation highlights the necessity for developing user-friendly tools and detailed documentation related to Explainable Artificial Intelligence (XAI) libraries. Enhanced usability can expedite the adoption of Explainable Artificial Intelligence (XAI) by reducing the obstacles preventing individuals from engaging with the technology.

The need for more enquiries about utilizing eXplainable Artificial Intelligence (XAI) approaches for enhancing application performance is noteworthy. This observation implies the existence of a yet unexplored domain for investigation. Future research in Explainable Artificial Intelligence (XAI) could prioritize the development of guidance and optimal methodologies for using these techniques to augment the performance of particular applications.

A wide range of enquiries indicates the dynamic nature of explainable artificial intelligence (XAI), necessitating ongoing revisions to established norms and optimal approaches. This suggests that there is a requirement to incorporate agile development principles in the techniques of Explainable Artificial Intelligence (XAI) to address and adapt to evolving difficulties and potential advancements effectively.

A comprehensive comprehension of these consequences is essential for researchers, educators, and practitioners who are deeply committed to successfully using XAI methodologies. The results of this study provide valuable insights that may be used to develop a strategic plan for tackling obstacles, enhancing educational efforts, and cultivating a cooperative environment to further the progress of XAI.

# 8 THREATS TO VALIDITY

## 8.1 Internal Validity

We utilize a filtering process to omit the frequently asked ones to mitigate the potential bias that may arise from selecting a non-representative collection of questions. Moreover, it is essential to acknowledge that a subset of the questions we have faced do not directly relate to the domain of XAI techniques. A comprehensive manual investigation was undertaken on all questions and responses to mitigate false-positive outcomes.

## 8.2 External Validity

To address the issue of representativeness in our study, we collect data from StackOverflow, a trendy online forum within the software development community. Nevertheless, the findings of our investigation could be more comprehensive in their generalizability. They can only be extrapolated to application programmers interested in XAI techniques on the StackOverflow platform. This statement does not encompass application programmers who utilize alternative question-and-answer platforms. Furthermore, our analysis is limited to enquiries and responses in the English language. While gathering data from other question-and-answer websites is feasible, we anticipate minimal deviations when evaluating solely English content.

# 9 CONCLUSION

The analysis of obstacles related to Explainable Artificial Intelligence (XAI), as documented on Stack Overflow, sheds light on the complex array of issues that developers confront when incorporating explainability techniques into AI systems. The investigation unveiled a range of prominent challenges, encompassing difficulties in installation, discrepancies in visualization, and obstacles in integrating models. The results highlight these difficulties' enduring and complex character, necessitating a sophisticated approach to their resolution. Moreover, the analysis has brought attention to areas where clear-cut solutions still need to be found, underscoring the importance of ongoing research and collaborative endeavours within the XAI community. This examination is a preliminary exploration aimed at cultivating a more profound comprehension of these problems and stimulating additional investigation to drive the progress and widespread implementation of explainable AI techniques in authentic contexts.

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