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Research Article

Explainable AI in Ad Enforcement: Striking the Balance Between Transparency and Safety

Binita Mukesh Shah
Affiliation: Independent Researcher, IEEE Member ID: 101290436
ORCID: 0009-0009-1555-9134
Email: binitashah6492@gmail.com

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ABSTRACT

The combination of Artificial Intelligence (AI) and advances in technology into the advertising platforms has changed the way policy enforcement works. AI offers scalability and improves efficiency in preventing bad actors from encroaching systems while protecting users from harmful content, however, this brings a new challenge in terms of opacity to legitimate advertisers. Explainable AI (XAI) gives a potential solution by offering some level of transparency into the AI world of enforcement and decision making. This paper talks about the benefits of XAI in ad enforcement, helping advertisers understand and correct their policy violations and in improving user trust through better ad disapproval explanation and recommendations to fix them. Along with the advantage of increased transparency, there are potential risks that need to be considered like exploiting of this information by malicious and bad actors. This paper focused on a tiered transparency framework for achieving a good balance between the transparency and protection problem in the implementation of XAI in the digital advertising landscape.

Keywords: AI, Ad Enforcement, Transparency

1. Introduction

Social media is prevalent all across now whether it's teenagers, adults or older people and each time we use social media or even do a basic search, we come across advertisements. Advertisements form the fundamental reason for the internet boom. These internet advertisements are everywhere and they follow you cross platform too in many instances. The reason why most of us have bought something from an ad and actually have not experienced fraud is because of the complex infrastructure and existence of Trust and Safety (T&S) teams working behind the scenes to ensure these ads are legitimate, safe and trustable. In a digital world, with so many scams and fraudulent actors, these teams serve as the first line of defense for both the users and the platform [1].

The days of reviewing manually each and every ad are far behind us in terms of scale and efficiency. In the current landscape, bad actors are advanced and use technologically advanced methods to circumvent platform safeguards and combat the protection in place. To combat this, T&S teams should adapt, learn and deploy sophisticated AI techniques to protect the platform and users [2]. But here is the part that is challenging, it is a high stakes technological race, where good advertisers can sometimes become collateral damage. They find themselves in the middle of this crossfire where their ads which are flagged either due to an error due to complicated systems or due to their lack of knowledge of policies are still penalized in the same way to ensure trust and transparency across advertisers. This process can be called over flagging where an ad which is non violating is incorrectly identified as problematic [3].

By understanding different systems and talking to different policy teams, I know they constantly wrestle with a fundamental question: how much information should they reveal about their enforcement decisions? Too little transparency leaves legitimate advertisers frustrated and powerless; too much might create a roadmap for bad actors to game the system [4].

This is where explainable AI will be helpful. As the name suggests, XAI attempts to demystify artificial intelligence by providing simple and easy to understand rationales for its decisions [5]. For advertisers, this means receiving clear explanations of why their ad was rejected—not just some generic policy reference, but specific guidance on what elements triggered the violation and how to fix them.

Beyond improving the advertiser experience, XAI can enhance user trust by explaining why an ad was shown to them and data usage more transparently [6]. This is something I've debated with colleagues for years as to what happens when bad actors leverage these explanations to circumvent detection? When does transparency begin to undermine safety? How do we calculate when one triumphs the other?

This paper examines both sides of this complex equation. I'll explore how XAI is transforming ad enforcement, analyze its benefits and risks, and propose a framework for balancing transparency with protection. The goal would not be to advocate for complete transparency at all costs, but rather to find that sweet spot where platforms can be transparent enough to help legitimate users while still maintaining necessary defenses against those with malicious intent [7]. Many companies are now adopting some behavior like this but there is always room for some improvement.

2. Background and Context

2.1. The Rise of AI in Digital Advertising

In today's world of digital advertising, Machine Learning and Artificial Intelligence plays a major role. Big companies like Google, Amazon, Meta use advanced and state of the art AI systems throughout their advertising pipeline, including placement of ads, targeted ads, enforcement of policies and fraud detection. A recent report published by the Interactive Advertising Bureau (IAB) shows that 87% of total spent for digital advertising is used for platforms powered by AI, which amounts to more than $280 billion globally (IAB, 2024) [8].

If we ask what is the primary advantage of using AI for enforcement of policies, the answer is scale. On a daily basis millions of ad submissions are processed by major platforms. This makes human review of these submissions unfeasible economically [9]. These AI models have the ability to evaluate these submissions in milliseconds using multi-dimensional frameworks built specifically for policies. Simultaneously these submissions are also evaluated against prohibited content checks, misleading claims and technical compliance, all in milliseconds [10].

In Spite of these advantages of using AI systems, more often than not these AI system operate as a "black box" where even the platform operators are in the blind when it comes to decision making process [11]. These can create few substantial challenges:

- Many legitimate advertisers cannot understand why their ads were rejected, and without a clear rejection explanation, they end up wasting resources performing trial and error fixes or unfortunately abandon the platform itself.
- Support teams of these platforms end up facing increased volume of enquiries by the advertisers due to lack of explanations given for rejections.
- Over a period of time these unexplained rejections can lead to the advertisers not trusting the platforms and their enforcement mechanisms.
- Lawmakers have been increasingly demanding transparency in these decision making which is done by algorithms, especially when these decisions can have an impact on economic opportunities [12].

2.2. Understanding Explainable AI (XAI)

Explainable AI (XAI) allude to techniques and method that can make the above mentioned decision making by AI more transparent and understandable to humans. Instead of just making a decision, XAI also aims to provide reasons, easily understandable by humans, that led to the decision [13].

In industries like finance and healthcare that are heavily regulated, it has become necessary to use XAI when it comes to compliance and risk management [14]. For instance, if a loan application is denied by AI, financial regulations may require that specific reasons that led to the denial should be provided to the applicant. Similarly a physician must get the reasons behind the recommendations made by AI powered medical diagnostic tools, which ensures appropriate care is given to the patients [15].

Digital Services Act (DSA) by the European Union has also made similar requirements fort the digital advertising, where in platforms are required to give "meaningful explanations" whenever a rejection occurs [16]. These regulatory requirements has led to am increased and quicker interest in XAI when it comes to ad enforcement.

The technical approaches for the XAI does differ widely across the field:

- Feature Importance Methods: Few techniques like Local Interpretable Model Agnostic (LIMA) and SHapley Additive exPlanations (SHAP) which identifies which of the inputted features had the most influence on a particular decision [17].
- Rule Extraction: This includes methods that extract human readable rules from complex models to provide estimate for the decision making [18].
- Counterfactual Explanations: This includes methods which can show how the inputs can be altered to get a different decision [19].
- Attention Visualization: Another technique when it comes to a deep learning model is visuals that can show which section of an input (image or text) has the model focused on when it made a decision [20].

XAI has the potential to provide specific and actionable feedback for policy violations to the advertisers. Instead of just knowing that an ad was rejected, this feedback can help them to understand which elements of their ad violated which specific policy and can help them to perform targeted corrections [21].

Talking about the end users, XAI enhances "Why am I seeing this ad?" experience by providing clear and specific explanations of targeting criteria, This kind of transparency helps in building trust and giving the user more meaningful control over their ad experience [22].

2.3. Challenges and Considerations

Despite of all the potential benefits that XAI provides, implementing it in ad enforcement poses many significant challenges:

- Security: Providing detailed and specific explanations can help the bad actors to find a way around the enforcement systems. If the scammers know which text or image has led to the rejection, they can code to dodge the triggers [23].
- Technical Complexity: State of the art ad review systems often use deep neural networks (DNN) or ensemble methods that can be difficult to interpret. Additional technical investment may be required to extract meaningful explanations from these complex systems [24].
- Explanation Quality: Explanations that are overly technical can confuse the advertisers whereas explanations that are overly simple can provide very little actionable guidance. Getting the right balance requires the understanding of both the practical needs of the advertisers and the technical aspects of the model [25].
- Information Asymmetry: All advertisers do not have the same level of technical knowledge. Larger businesses can have the expertise and resources to understand and take actions on detailed technical explanations whereas smaller businesses may require more simpler and descriptive guidance [26].
- Implementation Cost: Addition of XAI to already existing systems will require additional engineering resources and ongoing maintenance. This means significant investment for the platforms [27].

3. What is Explainable AI (XAI)?

Explainable XAI shows a subset of AI research which focused on making AI systems more transparent and decisions made by AI systems more understandable to humans. XAI methods aim to provide deeper insights into the "why" without revealing the nitty gritty details of internal workings of the complex systems used to enforce [28].

3.1. Key Components of XAI

Effective XAI systems in advertising typically involve several key components:

- Interpretability mechanisms: Using technical methods that create custom explanations from complex models, such as feature importance methods, rule extraction, or attention visualization [29].
- Translation layer: System components that convert technical explanations into human-readable format, tailored to the audience needs (e.g., technical teams vs. small business advertisers vs individuals vs large technical corporations) [30].
- Contextual awareness: The option to consider details around an ad rejection which include advertiser's past history, the type of business model and vertical and specific policies that are violated in the given situation [31].
- Actionability focus: Providing explanations that help advertisers to make actionable decisions to resolve issues faster rather than giving explanations that give little to no information [32].

3.2. XAI Methods in Advertising

Several XAI methodologies have shown particular promise in digital advertising contexts:

- Feature importance visualization: Specifying or showing which component of an ad were most likely to cause the rejection or disapproval. (e.g images, text, video, landing page component) [33].
- Policy-specific explanations: Giving specific policy violations that give clear and relevant articles to documentation so advertisers can fix issues quickly [34].
- Counterfactual examples: Demonstrating the difference between what passes checks vs what doesn't, giving examples of what could pass review and why the given ad didn't by showcasing the minor differences [35].
- Confidence scoring: Showing the probability of accuracy of the model decision accuracy and giving the option for the advertisers to trigger human review in certain cases based on model score [36].

3.3. The Importance of XAI in Digital Advertising

The benefits of implementing XAI in advertising enforcement extend beyond regulatory compliance:

- Reduced support burden: More transparency, means less questions meaning less need for the support team or other operational dependencies [37].
- Faster resolution times: Due to the volumes, time zones and triaging across teams, usually a human resolved case would take much longer than providing a self-serve help tool at the disposal of the advertisers [38].
- Higher advertiser retention: Platforms giving the level of transparency and providing self help tools create a better advertiser experience and advertisers are more likely to stay with the platform due to the customer satisfaction [39].
- Improved model performance: Models are as good as the data that's fed into it, and with this real time live data with feedback from actual advertisers can help identify model weaknesses and continually improve model performance [40].
- Consumer trust: Users also would appreciate transparency in the system as to why an ad was shown, what kind of data about them is being used, thus improving data privacy and transparency [41].

4. Real-World Applications of XAI in Advertising

The implementation of XAI in the advertising world has already seen some benefits across many dimensions in the digital ads ecosystem.

4.1. Automated Policy Explanations

Modern technology uses complicated systems to ensure advertisers get almost real time feedback on their ads regarding any policy violations.

- Policy-specific violation details: This includes which policies are violating, what does the policy mean and also direct links to documentation giving more details about the policy to enhance understanding [42].
- Multi-modal highlighting: The specific elements that potentially caused the violation like text or images or videos [43].
- Severity indicators: There are also systems that tell what the severity of the violation is which can cause from approved in some places to disapproved in all [44].
- Suggested fixes: Providing self help tools using AI that generate recommendations to modify the given ads such that they comply with the policies [45].

4.2. User-Facing Transparency

XAI is also trying to improve transparency for ad viewers or users of he internet with a detailed and improved explanation on "Why am I seeing this ad"?" This includes:

- Detailed targeting explanations: We all want to know more and not just the typical "based on your interest" but "because you showed interest in buying a wedding dress on April 10" [46].
- Control mechanisms: Giving users the option to choose and adjust what their preferences in terms of targeting are directly in the interface [47].
- Feedback loops: Help users to provide feedback on what was useful, what they would like to see more and what they would not like to see in the future targeting decisions [48].

4.3. Landing Page Analysis

A particularly promising application of XAI is in landing page analysis, where AI systems can:

- Identify specific compliance issues: With the complex nature of websites and especially the larger organizations having so much content on their landing pages, it is important and easy for them to know which exact place on the landing page is causing the issue (e.g., missing privacy policies, misleading claims, broken checkout flows) [49].
- Provide visual guidance: Using heat maps or simulated experiences from a user point of view to highlight areas of the landing page where the issue persists [50].
- Suggest technical fixes: Giving a technical mode to resolve issues like image resolution, cross device compatibility [51].

4.4. Self-Help Tools

XAI is also powering a new generation of self-help tools for advertisers, including:

- Interactive policy guides: Providing policy precheck tools where advertisers can run their content through the tool before even submitting [52].
- Violation databases: Finding common violations like FAQs but for policy violatons with examples and what worked as resolution for others [53].
- Predictive warnings: Systems that flag what could be an issue during ad creation so before submission those can be fixed [54].

5. Risks and Trade-Offs: Transparency vs Protection

The value of high-quality explanations to advertisers and users is definitely high, implementing these explanations isn't without significant challenges. To implement these however, there are some complex trade-offs between transparency and protection that platforms must navigate [55].

In my experience working with complicated systems and being an internet user, I've repeatedly witnessed the tension between privacy teams advocating for protection and customer service teams pushing for transparency. Both sides have strong arguments and finding the correct balance or sweet spot depends on egregiousness of the content and the risk assessment [56].

5.1. Security Concerns

The main concern with transparent and detailed explanations is it can provide a roadmap or hint for bad actors to navigate and circumvent the enforcement system enabled for user protection. These risks include:

- Evasion techniques: Using detailed explanations to do trial and error and find a way to escape the detection the system has in place and harm users [57].
- Pattern identification: Collecting and storing different examples of past violations and explanations and then using that to exploit the systems [58].
- Vulnerability mapping: Providing a detailed explanation on what can reveal blind spots in the enforcement systems [59].
- Adversarial attacks: Using the data provided to build custom combat systems to deliberately bypass detection systems and cause user harm and perform fraudulent activities at a larger scale [60].

5.2. Information Asymmetry

Each advertiser is different in terms of the needs and capabilities and so the explanations that they would need also cannot be one size fits all approach:

- Large agencies have dedicated people who are policy and technical experts and can interpret explanations and also suggest fixes easily [61].
- Small businesses don't have a dedicated team or the level of expertise and they would benefit from more custom, simple and detailed guidance [62].
- The need-based occasional advertisers can just do with basic content or help center articles for specific violation information [63].
- Bad actors who are the highest risk for exploitation will cause the most harm with detailed explanations [64].

This asymmetry suggests that a one-size-fits-all approach to XAI may be suboptimal, and that explanation depth might need to vary based on advertiser characteristics and past behavior [65].

5.3. Cost-Benefit Analysis

Implementing XAI systems requires significant investment in:

- Technical infrastructure: Creating, deploying and testing systems that generate explanations to work alongside enforcement models [66].
- User interface development: Creating user friendly interfaces that can help present the information in a quick, easy to understand and interpret way [67].
- Ongoing maintenance: Keeping the systems updated with recent trends, feedback and continually monitoring and improving them [68].
- Quality assurance: Getting qualitative and quantitative feedback by doing data analysis and conducting surveys to ensure usability across the advertisers and users [69].

These costs must be weighed against the benefits in terms of:

- Reduced support costs: Fewer tickets, fewer human intervention and faster resolution times [70].
- Improved advertiser retention: Higher long-term platform revenue and advertiser trust and customer satisfaction score [71].
- Regulatory compliance: Meeting continually emerging legal requirements for transparency [72].
- Enhanced platform trust: Building better and trusted relationships with advertisers and users [73].

6. Case Examples & Anecdotes

To demonstrate the real world impact of explanation quality, there are many contrasting cases from my research, for example:

6.1. The Impact of Poor Explanations

A small business that specializes in natural skincare made from organic ingredients suddenly experienced many rejections in their entire ad catalog. This caused a dip in their traffic and revenue and when looked to find the root cause they got a very generic explanation: "Disapproved: Healthcare policy violation:

The business owner was confused, as they sold skincare products, and had nothing to do with any healthcare items. Initially they thought it would be a system issue which will resolve itself but it was a week and still the issue was present. At this time they decided to contact support and after weeks of back and forth the support agent could finally tell the owner that the issue was because one product description on their website mentioned an ingredient that had "anti-inflammatory properties", which triggered a healthcare policy violation [74].

This lack of specificity cost the business an estimated $12,000 in lost revenue and required approximately 80 hours of support team time to resolve. The business owner also during this time considered abandoning the platform due to this experience.

For this business owner, it was not just the loss in revenue that caused the frustrating experience but it was the feeling of being completely powerless to fix the problem [75].

6.2. The Value of Detailed Explanations

Now, another case was on the opposite end of the spectrum from the above. Their platform provided a specific explanation when their ad was rejected. The rejection specifically said "Healthcare claim detected: The phrase "Reduces Inflammation" on your website violates the healthcare claims policy.

With this detailed and specific guidance, the business was able to quickly identify the issue, modify the ingredient list and resubmit their ad. Their revised ad was approved within an hour and this caused minimum friction or impact on their ads. The business only took 20 minutes to identify the problem because of this clear guidance [76].

For this business owner, that explanation was like a roadmap - it took them to the problem, pointed out the fix and got the issue resolved in no time, there was no gap to be upset, worried or lose revenue at all [77].

6.3. Security Risk Example

Let's take an example of security concerns, where one platform implemented highly detailed explanations for ads related to financial services. After three months, they observed a huge uptick in escalations for the financial fraud policy and on assessing the root cause of this behavior they noticed a pattern of bad actors gaming the system. These bad actors had systematically tested and refined their deceptive looking ads to game the system based on the feedback received in the past. They slightly modified their old ads just making them good enough to bypass the system detection using the previous explanations [78].

This pattern caused a lot of user harm and the platform was forced to reduce explanation specificity for high-risk categories while still keeping detailed explanations for lower-risk categories and established advertisers [79].

These cases further strengthen the argument and the need for balanced approaches that can provide sufficient guidance for legitimate advertisers but still limit exploitation potential for bad actors in the ecosystem [80].

7. Frameworks for Balancing Transparency and Protection

Based on our research findings and industry observations, we propose a multi-layered framework for implementing XAI in ad enforcement that balances transparency needs with security concerns [81].

7.1. Tiered Transparency Framework

We propose a tiered approach to explanation transparency that adjusts based on risk assessment:

Tier 1: Basic Explanations (All Advertisers)

- Policy category identification
- General location of violation (ad text, image, landing page)
- Links to relevant policy documentation
- Self-help resources [82]

Tier 2: Detailed Explanations (Established Advertisers)

- Specific violation location (exact text, image element, or page location)
- Feature importance indicators
- Example alternatives that would comply
- Confidence scores for AI decisions [83]

Tier 3: Advanced Explanations (Trusted Partners)

- Technical details on model interpretation
- Counterfactual past examples
- Appeal likelihood assessment
- Pattern analysis across campaigns [84]

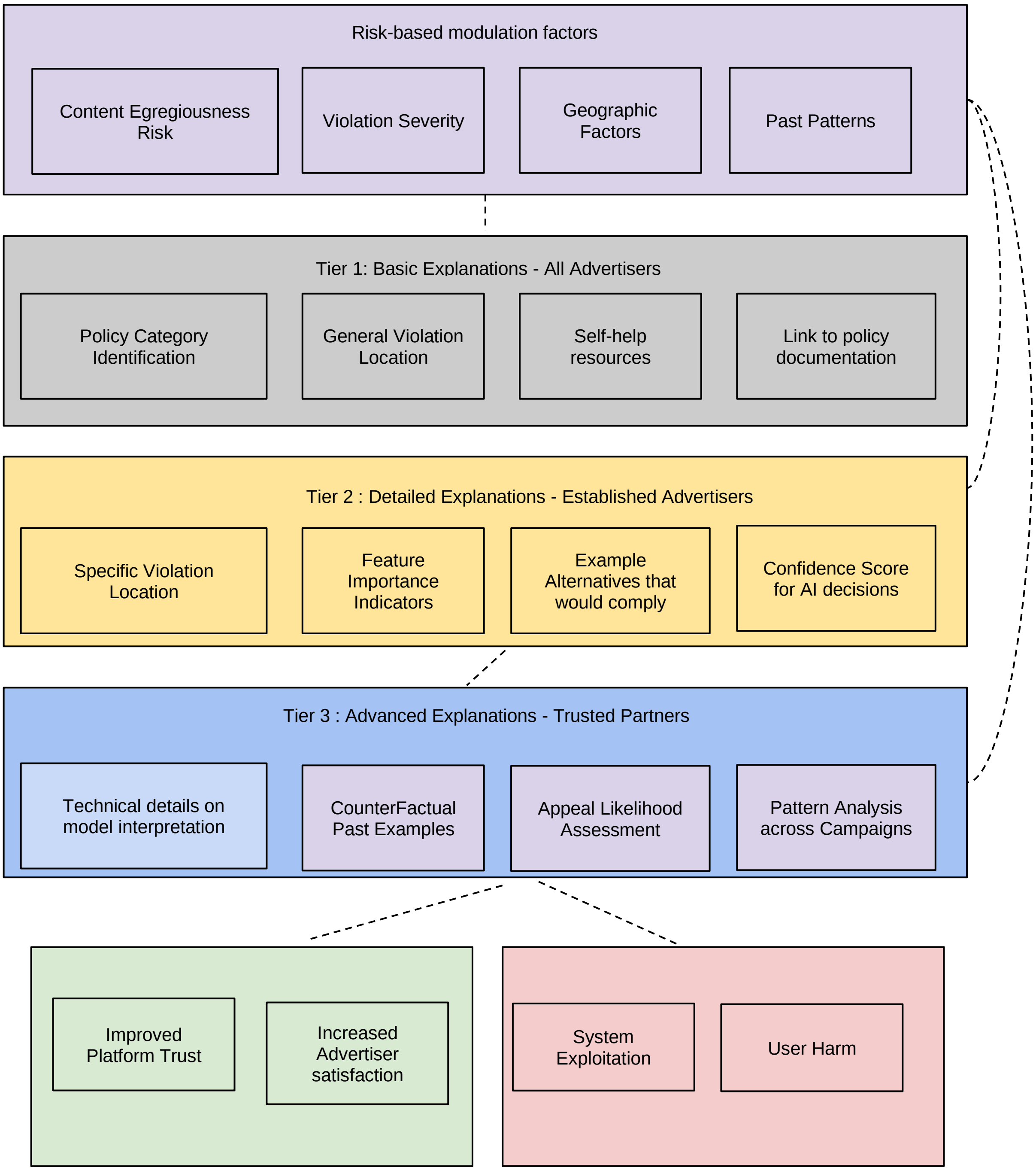
Risk-based modulation factors
Content Egregiousness Risk
Violation Severity
Geographic Factors
Past Patterns
Tier 1: Basic Explanations - All Advertisers
Policy Category Identification
General Violation Location
Self-help resources
Link to policy documentation
Tier 2 : Detailed Explanations - Established Advertisers
Specific Violation Location
Feature Importance Indicators
Example Alternatives that would comply
Confidence Score for AI decisions
Tier 3 : Advanced Explanations - Trusted Partners
Technical details on model interpretation
CounterFactual Past Examples
Appeal Likelihood Assessment
Pattern Analysis across Campaigns
Improved Platform Trust
Increased Advertiser satisfaction
System Exploitation
User Harm

Figure 1. Tiered Transparency Framework

This tiered approach allows platforms to provide basic transparency to all advertisers while reserving more detailed explanations for established accounts with proven compliance history to reduce risks and provide a positive advertiser experience [85].

7.2. Risk-Based Modulation

In addition to just the advertiser tier, explanation detail can be modulated based on:

- Content egregiousness risk: High-risk categories like financial services, healthcare, politics, and gambling might receive less detailed explanations due to higher exploitation potential [86].

- Violation severity: Critical violations (e.g., fraudulent content, scammy content) might receive less specific explanations than technical violations (e.g., image quality issues) [87].
- Geographic factors: Regions with a set of specific regulatory requirements might receive more detailed explanations to ensure compliance [88].
- Past patterns: Advertisers with patterns of repeated past policy violations might receive limited explanations until they establish a better compliance history or trust in the system [89].

7.3. Adaptive Learning Systems

To continuously improve the balance between transparency and protection, it is also recommended to implement:

- Feedback loops: Continuous data collection and feedback on whether explanations helped advertisers resolve issues and time taken to resolve [90].
- Exploitation monitoring: Tracking patterns and advertiser behaviors that might indicate explanation systems are being exploited to use that to detect abuse in advance [91].
- A/B testing: Systematically testing different explanation approaches to identify optimal strategies [92].
- Red team exercises: Proactively testing explanation systems for potential vulnerability and exploitation vectors [93].

This adaptive approach allows platforms to refine their explanation strategies based on real-world outcomes rather than static assumptions and continually adapt to the needs of the ecosystem [94].

8. Implementation Recommendations

Based on our research and experience in this system, the following recommendations would be beneficial for implementing XAI in ads enforcement:

Based on our research findings, we offer the following recommendations for implementing XAI in ad enforcement:

8.1. Technical Implementation

- Simple rule based system - We can use very simple heuristic rule based systems where explanations are easy and straightforward both to implement and understand [95].
- User friendly visualization tools - Invest in visualization tools that help highlight issues faster and make explanations easy to understand and action on. This can include highlighting, heat maps and even pointing to the right areas to focus on [96].
- Build modular systems: Adaptable and customizable systems that change based on advertiser tier and risk assessment [97].
- Incorporate feedback mechanisms: Constant feedback loops and surveys which can help improve and enhance systems by continually modifying and improving systems [98].

8.2. Operational Considerations

- Train support teams: Enhance the support teams knowledge by training and evaluation to help support advertisers and supplement the automated systems when required [99].
- Establish escalation paths: Make clear pathways and processes for cases when XAI system explanations are not enough [100].
- Monitor explanation quality: Have audit processes to ensure accuracy, clarity and actionability [101].
- Document explanation limitations: Communicate openly on what and what cannot be shared for advertiser understanding and better relationship management [102].

8.3. User Experience Design

- Contextual delivery: Present explanations in the context where advertisers need them (e.g., in the ad creation flow) [103].
- Progressive disclosure: Use expandable sections to allow advertisers to access additional detail as needed [104].
- Plain language focus: Prioritize clear, non-technical language in explanations [105].
- Multimodal presentation: Combine text explanations with visual indicators for maximum clarity [106].

8.4. Measurement Framework

To assess the impact of XAI implementation, we recommend tracking:

- Resolution time: Time taken for advertisers to resolve policy issues after they received an explanation from our implemented systems [107].
- Support volume: Reduction in support tickets for policy related questions [108].
- Appeal rates: Reduced number of unsuccessful and unnecessary appeals [109].
- Advertiser satisfaction: Customer satisfaction scores for explanation quality [110].
- Platform trust: Improvement of trust scores and sentiment analysis across users and advertisers [111].
- Security indicators: Threats and escalations caused by bad actors misusing and abusing the system [112].

Regular review of these metrics can help platforms continuously refine their approach to XAI implementation [113].

9. Researcher's Perspective

I wanted to offer some personal thoughts and insights I gained from doing this research before I wrap up. I began this as a technical study of XAI systems, but it soon became apparent that millions of advertising worldwide deal with this human problem on a daily basis. Due to opaque enforcement procedures, it is not only a technical problem but can also have an emotional toll on small business owners, particularly those who invest in digital advertising to gain international recognition [114].

This is not just about making revenue for small business owners or the larger corporations but there are non profit organizations whose campaigns get rejected with vague explanations. Each day the campaign is not run, it could mean fewer donations for people in need like disaster victims. I could not understand the impact of this problem until I started researching about this in detail. This is when I realized that it wasn't just a technical problem; it was affecting real people in meaningful ways [115].

At the same time, my discussions with T&S professionals revealed genuine concern about exploitation. "We've seen firsthand how quickly bad actors adapt," one engineer told me. "Sometimes withholding information feels like the only way to keep people protected." [116]

This research has convinced me that the transparency-protection balance isn't just a technical problem - it is a fundamental debate between values and priorities. When we design these systems, we make implicit decisions on what is important, what risks we are willing to take and if we take the risk what could be the potential impact. I hope this paper contributes to those decisions which can be a balance of user protection and transparency [117].

10. Limitations and Future Work

With any research, the study has limitations and that can inform any future work in the space. The data is based on experience and interviews and I have tried to cover a diverse range of people across the spectrum, future research should specifically examine the experiences of advertisers in regulated sectors like finance, healthcare and regional policies [118].

Additionally, our analysis focused primarily on advertiser and user perspectives rather than on security outcomes. To assess risk and user harm it would be important to study exploitation attempts before and after XAI implementation. This would provide valuable insights into actual security risks rather than theoretical concerns [119].

I'm interested in further adaptive explanation systems that can dynamically adjust transparency based on real time risk evaluation for dynamic categories. We would need systems that potentially deliver more transparency to the advertisers but still keep the users protected from online fraud or harm [120].

11. Conclusion

As digital advertising becomes more and more AI-driven, the need for this explainability in enforcement systems becomes crucial. The research demonstrates that high quality explanations deliver long term benefits to users, advertisers and the platforms by reducing resolution times, decreasing support costs, increasing advertiser satisfaction and improving user trust in the platform [121].

The benefits are definitely worthy but we should not forget the legitimate security concerns, especially for the bad actors who can try to exploit the explanations. The frameworks proposed in the paper aim at tiered transparency and risk based modulation. This offers practical approaches to strike this balance [122].

Online advertising will inevitably be more transparent in the future than it was in the past. Demands from users, advertisers, and regulators all suggest that explainability standards should be raised. In addition to satisfying these external demands, platforms that make an investment in careful XAI implementation now will also see major operational gains [123].

Instead of perfect transparency, which would probably result in intolerable security risks, the objective is optimal transparency, which is adjusted to optimize advantages while reducing the possibility of exploitation. Platforms can build a more transparent and secure advertising ecosystem by implementing subtle, flexible approaches to XAI [124].

Ongoing research will be necessary to improve these strategies and create new methods for striking a balance between protection and transparency as XAI technology develops. These developments have enormous potential benefits for the advertising sector [125].

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