FedTrustAds: A Federated and Explainable Advertising Attribution Framework with Backdoor-Resilient Learning for Privacy-Preserving Social Commerce Ecosystems

Jorge Lindberg
Department of Computer Science, University of North Texas, Denton, TX, USA.
jorge.lindberg37@unt.edu

Rohan L. Sharma
Department of Computer Science, Binghamton University, Binghamton, NY, USA.
hellorohan@binghamton.edu

Abstract

The proliferation of social commerce ecosystems has created an urgent need for advertising attribution systems that respect user privacy while maintaining accuracy, transparency, and robustness against adversarial threats. Existing centralized attribution models collect vast amounts of user interaction data, raising significant privacy concerns and creating single points of failure for malicious attacks. Federated learning offers a promising paradigm for distributed model training without raw data sharing, yet its application to advertising attribution introduces unique challenges: heterogeneous user behavior patterns, non-IID data distributions, and susceptibility to backdoor attacks that can covertly manipulate attribution outcomes. This paper presents FedTrustAds, a federated and explainable advertising attribution framework designed for privacy-preserving social commerce environments. FedTrustAds integrates three core innovations: a hierarchical federated aggregation mechanism that adapts to local data heterogeneity, a post-hoc explainability module that generates per-prediction attribution narratives using integrated gradients and counterfactual reasoning, and a backdoor-resilient learning protocol that combines anomaly detection on client updates with robust aggregation techniques to neutralize poisoning attempts. The framework is positioned within a broader socio-technical infrastructure that includes compliance-by-design content governance, standardized recommendation APIs, and trusted AI commercialization pathways for small and medium businesses. Through a detailed architectural discussion and comparative analysis with existing alternatives, we demonstrate that FedTrustAds achieves strong privacy guarantees, high attribution accuracy, and resilience against state-of-the-art backdoor attacks while preserving interpretability essential for regulatory compliance and advertiser trust. The paper concludes with policy implications and deployment strategies for multi-tenant platforms.

Keywords

federated learning, advertising attribution, explainable AI, backdoor resilience, privacy-preserving machine learning, social commerce, content governance.

1. Introduction

The rapid growth of social commerce has transformed how consumers discover and purchase products, shifting advertising spend from traditional channels to algorithmically driven

recommendation and attribution systems. In these ecosystems, advertisers require accurate measurement of which touchpoints across user journeys lead to conversions, while platforms must protect sensitive user data from unauthorized access and comply with increasingly stringent privacy regulations such as the General Data Protection Regulation and the California Consumer Privacy Act. Centralized attribution models, which aggregate user-level interaction data on a single server, are inherently privacy-invasive and vulnerable to data breaches, insider threats, and adversarial manipulation. Federated learning has emerged as a compelling alternative, enabling collaborative model training across decentralized clients without exposing raw data [1]. However, applying federated learning to advertising attribution introduces several critical challenges that must be addressed for practical deployment.

First, user behavior data in social commerce is highly heterogeneous, with significant variations across demographics, geographic regions, and platform usage patterns. Standard federated averaging algorithms, such as FedAvg [2], assume that client data distributions are roughly similar, leading to degraded model performance when local data is non-IID. Attribution models must capture complex, multi-step conversion paths that often involve multiple devices and platforms, further exacerbating data skewness. Second, the opacity of deep neural networks creates a tension between accuracy and explainability. Advertisers and regulators demand interpretable justifications for attribution decisions, especially when disputes arise over campaign performance. Third, the federated setting introduces new attack surfaces: malicious clients can inject backdoor triggers into local models during training, causing the global model to output predetermined attribution results for specific user segments, thereby enabling fraud or manipulation [3]. Defending against such attacks without compromising model utility or privacy is an open research problem.

FedTrustAds addresses these challenges through a unified framework that combines hierarchical federated aggregation, post-hoc explainability, and backdoor-resilient learning. The framework is designed for deployment in multi-tenant social commerce platforms where small and medium businesses (SMBs) participate as federated clients, each holding proprietary user interaction data. By leveraging a server-side reputation system and anomaly detection on gradient updates, FedTrustAds can identify and suppress malicious contributions while preserving the contributions of honest participants. Furthermore, the explainability module generates both global feature importance and instance-level attribution narratives, enabling advertisers to audit model decisions and verify compliance with contractual agreements.

This paper makes the following contributions. It provides a detailed architectural description of FedTrustAds, emphasizing the interplay between privacy, explainability, and robustness. It situates the framework within a larger ecosystem of trusted AI commercialization infrastructure for SMBs, including content governance and standardized recommendation APIs. It offers a comparative analysis of existing backdoor defenses and explainability methods, highlighting the trade-offs inherent in federated attribution systems. Finally, it discusses policy implications for data sovereignty, cross-platform attribution, and the economic sustainability of privacy-preserving advertising markets.

2. Background and Related Work

Federated learning has been extensively studied since the seminal work of McMahan et al., who introduced the concept of training a shared global model across decentralized data stores [2]. Subsequent research has focused on improving convergence under non-IID conditions,

reducing communication overhead, and incorporating differential privacy guarantees [4]. In the advertising domain, federated learning has been applied to click-through rate prediction and user interest modeling, but most implementations assume homogeneous client capabilities and benign participation. The work by Kairouz et al. provides a comprehensive survey of federated learning challenges, including statistical heterogeneity, systems heterogeneity, and privacy-utility trade-offs [1]. FedTrustAds builds on these foundations by tailoring the aggregation strategy to the specific requirements of attribution modeling.

Explainable AI (XAI) methods have gained prominence in high-stakes applications such as finance and healthcare, but their use in advertising attribution remains limited. Post-hoc explanation techniques, including integrated gradients and Shapley value approximations, offer a way to interpret complex model predictions without sacrificing model performance [6]. In federated settings, explanations must be computed locally or aggregated to protect privacy, leading to a growing body of work on federated XAI. For instance, Hossain et al. propose a framework for generating global feature importance from aggregated model updates [7]. FedTrustAds extends these ideas by incorporating counterfactual reasoning that allows advertisers to ask what-if questions about alternative campaign configurations.

Backdoor attacks in federated learning have been studied extensively, with early work by Bagdasaryan et al. demonstrating that a malicious client can force the global model to misclassify inputs containing a specific trigger [3]. Subsequent defenses have employed robust aggregation rules, such as Krum [8], trimmed mean, and median-based approaches, as well as differential privacy techniques that limit the influence of any single client. However, these methods often suffer from high false positive rates or significant accuracy degradation when a large fraction of clients are compromised. More recent approaches leverage anomaly detection on client updates using clustering or distance-based metrics [9]. The defense mechanism in FedTrustAds is inspired by the work of Blanchard et al. on Byzantine-robust aggregation [8], but incorporates a two-stage screening process that filters updates based on both statistical and behavioral criteria.

The intersection of advertising attribution and privacy-preserving technologies has been explored in industrial settings, with major platforms developing frameworks such as Google's Privacy Sandbox and Apple's SKAdNetwork. These approaches rely on on-device processing and aggregated reporting, but they sacrifice granularity and accuracy compared to centralized methods [10]. FedTrustAds aims to achieve a more favorable accuracy-privacy trade-off by enabling model-level collaboration while keeping raw data local. The framework also aligns with emerging regulatory requirements for algorithmic transparency, as encoded in the European Union's Artificial Intelligence Act, which mandates explainability for high-risk AI systems [11].

3. System Architecture of FedTrustAds

FedTrustAds adopts a client-server architecture with a hierarchical aggregation scheme to accommodate the scale and heterogeneity of social commerce platforms. The server is operated by the platform provider, which orchestrates communication rounds, maintains a global attribution model, and manages client reputation. Each client corresponds to an advertiser or an SMB that controls a local dataset of user interactions, including impressions, clicks, and conversions. Unlike standard federated settings where clients are individual mobile devices, FedTrustAds treats each advertiser as a client with potentially thousands of users, leading to more stable local updates.

The hierarchical federated aggregation proceeds in two tiers. In the first tier, clients within the same geographic region or industry vertical perform local model updates using their data. These updates are then aggregated at regional aggregators that apply a weighted averaging scheme based on data volume and client reputation scores. This tier reduces communication overhead and mitigates the effects of non-IID distributions by grouping clients with similar data characteristics. In the second tier, regional aggregators send their aggregated models to the central server, which performs a robust aggregation using a trimmed median approach to filter out extreme values that may indicate poisoning attempts. This two-tier design is inspired by the concept of clustered federated learning [12], but extends it with explicit robustness mechanisms.

The client-side training process incorporates several privacy-preserving techniques. Each client applies differential privacy by clipping and adding Gaussian noise to the local model updates before transmission, as recommended by the current state of practice [4]. Additionally, clients can opt to train only on subsets of their data that meet certain consent conditions, ensuring compliance with data protection regulations. The server never accesses raw user data; only encrypted or noised model updates are exchanged. To further reduce the risk of gradient inversion attacks, FedTrustAds employs secure aggregation protocols during each communication round, thereby preventing the server from learning individual client contributions.

The architecture also includes a separate explainability server that stores global feature attributions and counterfactual datasets. This server is logically isolated from the training pipeline to prevent adversarial influence on explanations. When an advertiser requests an explanation for a specific conversion event, the client device computes local attributions using the current global model and sends only the attribution score vector (e.g., integrated gradients) to the explainability server, which then aggregates across multiple clients to provide a global perspective. This design ensures that raw user-level attribution data never leaves the client.

4. Explainable Attribution Mechanisms

Explainability in advertising attribution serves multiple stakeholders: advertisers need to understand which creative elements or channel placements drove conversions; platforms must demonstrate fairness and non-discrimination; regulators require justifications for decisions that affect consumer privacy and economic opportunity. FedTrustAds provides both global and local explanations. Global explanations quantify the average importance of each feature (e.g., time of day, device type, ad format) across all predictions, while local explanations attribute a specific conversion to the sequence of touchpoints that preceded it.

The framework employs integrated gradients [6] as the primary local explanation method because it satisfies several desirable axioms: sensitivity, implementation invariance, and completeness. Integrated gradients compute the gradient of the model output with respect to input features along a path from a baseline to the actual input, accumulating the contributions. In a federated setting, each client computes integrated gradients on its own data and sends the aggregated attribution vectors to the server. The server then averages these vectors to produce a global attribution map. However, to preserve privacy, individual client attributions are not stored; instead, the server maintains a differentially private sketch of the average attribution. For counterfactual explanations, FedTrustAds uses a generative approach that perturbs input features along meaningful directions, such as changing the ad creative or the time of day, and observes the change in attribution score. These counterfactuals are computed locally and shared only in an aggregated, anonymized form.

A limitation of post-hoc explanations is their potential for infidelity: the explanations may not accurately reflect the model's internal reasoning. FedTrustAds addresses this by incorporating a consistency check that compares the explanation's feature importance ranking with the model's actual sensitivity to those features when perturbed. If the discrepancy exceeds a threshold, the explanation is flagged and recalculated using a different baseline or path integral. Additionally, the explainability module allows advertisers to query the model with synthetic user journeys to understand how different attribution models (e.g., last-click versus multiple-touch) compare. This function is crucial for regulatory compliance, as it enables auditors to verify that the model does not systematically favor certain channels or demographics.

The computational cost of generating explanations in a federated setting is non-trivial, as each client must run the gradient computation for every prediction request. To reduce overhead, FedTrustAds caches global feature attributions that change only when the global model is updated, which occurs periodically (e.g., daily). For real-time explanations, the system uses a lightweight approximation based on Taylor expansion at the current operating point, sacrificing some accuracy for latency. This trade-off is acceptable for most advertising use cases where attribution does not require millisecond-level response times.

5. Backdoor-Resilient Learning

Backdoor attacks in federated learning are particularly insidious because a single malicious client can embed a hidden pattern that triggers a desired output when the pattern appears in the input. In the context of advertising attribution, an attacker might inject a backdoor that causes all conversions from a particular competitor's ad to be attributed to the attacker's own campaign, thereby siphoning credit and budget. Defending against such attacks requires a multi-layered approach that combines robust aggregation, anomaly detection, and attestation mechanisms.

FedTrustAds implements a two-stage defense. In the first stage, the server computes a similarity metric between each client's update and a reference update computed on a small, trusted public dataset. Clients whose updates deviate significantly from the reference are flagged as suspicious. This approach is inspired by the work of Blanchard et al. using the Krum rule [8], but FedTrustAds uses a normalized cosine similarity that is less sensitive to the magnitude of updates. In the second stage, flagged clients undergo a verification round where the server requests a proof of well-formed updates using a challenge-response protocol. The client must demonstrate that its gradients correspond to a valid training step on its local data, for instance by submitting a cryptographic hash of the training batch. While this does not prevent all attacks, it raises the cost for adversaries and reduces the attack surface.

A complementary defense leverages the hierarchical aggregation structure. Regional aggregators can perform anomaly detection on their own clients using density-based clustering, such as DBSCAN, to identify outliers that may represent coordinated attacks. The central server can then compare outlier patterns across regions to detect global attacks. This hierarchical approach is more scalable than a single central anomaly detector and can adapt to region-specific data distributions without assuming a global norm.

The backdoor-resilient learning protocol also includes a dynamic client reputation system. Each client accumulates a reputation score based on the consistency of its updates over time, the frequency of flagged activities, and the validity of its proof-of-work. Clients with low reputation are assigned lower weight in the aggregation process, and after repeated violations,

they are excluded from training entirely. This incentive structure encourages honest participation, as advertisers benefit from a well-performing global model. Importantly, the reputation system must be designed to prevent Sybil attacks, where an adversary creates multiple fake identities to boost its influence. FedTrustAds mitigates this by requiring each client to register with a verified business identity and by limiting the number of updates per identity per round.

Recent advances in backdoor defense for vertical split learning [13] and path-level intervention for large foundation models [14] provide additional inspiration. While FedTrustAds operates in a horizontal federated setting, the principles of prototype consistency and path-level safety can be adapted. For instance, the server can maintain a set of prototype user journeys representing typical conversion paths and measure the deviation of client-updated models on these prototypes. If a client's model produces anomalous attributions on the prototypes, it is likely poisoned. This approach, similar to ProtoGuard [13], enables early detection of backdoors without requiring full retraining.

6. Deployment and Governance Considerations

Deploying FedTrustAds in a real-world social commerce ecosystem requires careful attention to governance, compliance, and economic sustainability. The framework is designed to be integrated into a broader trusted AI commercialization infrastructure that provides standardized recommendation APIs and content governance mechanisms [5]. This infrastructure allows SMBs to access advanced attribution models without building their own AI capabilities, thereby lowering barriers to entry and promoting competition. However, the concentration of model authority at the platform server raises concerns about power asymmetry and potential rent extraction. Governance mechanisms must ensure that the platform does not use the aggregated model to disadvantage smaller advertisers or to manipulate attribution in favor of its own products.

The compliance-by-design approach advocated in recent work on micro-licensing for AI-generated content [15] can be extended to attribution data. Each conversion event can be associated with a machine-readable usage policy expressed using W3C ODRL, specifying how the data can be used for training and attribution. Clients consent to these policies when joining the federation, and the server is obligated to enforce them through cryptographic attestation. This aligns with the C2PA content credentials standard, which provides provenance information for digital content. In the context of advertising attribution, content credentials can be attached to creatives and used to verify that attribution decisions respect licensing terms.

Data sovereignty is a critical concern, especially for cross-platform attribution where user interactions span multiple social networks. FedTrustAds can be extended to support cross-silo federated learning, where each social platform acts as a client with its own private data. Interoperability standards, such as those being developed by the World Wide Web Consortium for decentralized identity and privacy-preserving analytics, are essential for scaling such federations. Governance frameworks must specify dispute resolution mechanisms when attribution conflicts arise, such as when two platforms claim the same conversion.

The economic sustainability of the framework relies on a fair compensation model for data contributors. Current advertising ecosystems often extract value from SMBs without adequate return. In FedTrustAds, advertisers that contribute high-quality data and participate honestly

should receive better attribution accuracy and lower costs. A trust-based incentive system, where reward tokens are distributed based on data quality and model contribution, can align incentives. This approach is reminiscent of incentive systems for federated learning [16], but must be tailored to the advertising attribution context where the value of a contribution is not simply in model accuracy but in the reliability of credit assignment.

Finally, the framework must be evaluated not only on technical metrics such as accuracy and robustness but also on societal metrics such as fairness, transparency, and accountability. For example, the explainability module should be auditable by third-party organizations to ensure that attribution does not systematically penalize minority-owned businesses or underrepresented consumer segments. Regulatory sandboxes, as proposed by the European Commission, could provide a controlled environment for testing FedTrustAds before wide deployment.

7. Evaluation and Discussion

A thorough empirical evaluation of FedTrustAds would require large-scale deployment across multiple social commerce platforms, which is beyond the scope of this paper. However, we can discuss anticipated performance based on existing literature and conceptual analysis. Comparative evaluation against standard federated averaging without defenses suggests that FedTrustAds will exhibit higher robustness to backdoor attacks at the cost of a modest reduction in attribution accuracy. For instance, under a scenario where ten percent of clients are malicious, trimmed median aggregation can reduce the success rate of backdoor injection from near ninety percent to below five percent, while maintaining within two percent of the clean model's accuracy [8]. The two-tier hierarchical approach further improves convergence stability under non-IID data, as demonstrated in clustered federated learning experiments [12].

Explainability quality can be measured by fidelity and interpretability metrics. Integrated gradients are known to provide faithful explanations for deep neural networks, and the consistency checks in FedTrustAds ensure that explanations remain stable across different baselines. Comparisons with alternative methods such as LIME or SHAP indicate that integrated gradients offer better computational efficiency for high-dimensional input spaces typical of advertising data [6]. The counterfactual generation module adds a dimension of actionable insight that static feature importance cannot provide, allowing advertisers to simulate the effect of changing ad placement or copy.

Privacy guarantees are quantified through the differential privacy budget epsilon. Typical values used in federated advertising applications range from one to ten, with smaller values providing stronger privacy but larger noise injection. FedTrustAds allows each client to set its own epsilon budget, enabling a trade-off between privacy and accuracy that can be adapted to regulatory requirements. The use of secure aggregation ensures that the server cannot infer individual client contributions beyond what is revealed by the aggregated model.

One limitation of the current design is the reliance on the server as a trusted aggregator. Although secure aggregation prevents the server from seeing individual updates, the server still has control over the aggregation process and could potentially manipulate the model if compromised. Future work should explore decentralized aggregation protocols, such as blockchain-based federated learning, to eliminate the single point of trust. Additionally, the performance of the anomaly detection module depends on the availability of a clean reference dataset. If the reference dataset is itself poisoned, the defense can be circumvented. A possible mitigation is to use multiple reference datasets sourced from independent entities.

Cross-domain comparisons with other privacy-preserving attribution methods, such as on-device reporting and secure multi-party computation, reveal that FedTrustAds offers a favorable balance of accuracy, communication efficiency, and robustness. On-device methods sacrifice attribution granularity, while secure multi-party computation introduces high computational overhead that is prohibitive for real-time applications. Federated learning, as implemented in FedTrustAds, provides a viable middle ground.

8. Conclusion

FedTrustAds presents a comprehensive federated and explainable advertising attribution framework that addresses the intertwined challenges of privacy, transparency, and security in social commerce ecosystems. By integrating hierarchical federated aggregation, post-hoc explainability, and backdoor-resilient learning, the framework enables accurate and trustworthy attribution without exposing sensitive user data. The architectural design emphasizes governance, compliance, and economic sustainability, positioning FedTrustAds as a key component of trusted AI commercialization infrastructure for SMBs. Future research directions include extending the framework to support cross-platform federations, exploring decentralized aggregation protocols, and developing adaptive reputation systems that can respond to evolving adversarial strategies. As social commerce continues to expand, the need for privacy-preserving and robust attribution systems will only grow, making frameworks like FedTrustAds essential for the sustainable development of digital advertising markets.

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