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Privacy-Enhanced Ad Targeting for Social E-Commerce: A Federated Learning Framework with Zero-Knowledge Verification for Creator Monetization

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Abstract

The convergence of social networking and electronic commerce has given rise to the social e-commerce paradigm, where content creators serve as the primary drivers of consumer engagement and purchase decisions. However, this ecosystem faces a critical tension between the need for high-precision ad targeting to sustain monetization and the increasingly stringent requirements for user privacy preservation. Traditional centralized recommendation systems require the aggregation of massive user behavioral datasets, creating significant risks of data leakage and violating emerging regulatory frameworks. To address this challenge, we propose a novel framework titled Fed-ZKC (Federated Zero-Knowledge Creator). This architecture synergizes Federated Learning (FL) with Zero-Knowledge Proofs (ZKP) to enable privacy-preserving ad targeting while ensuring verifiable monetization attribution for creators. In our system, user preference models are trained locally on edge devices to prevent raw data transmission, while a cryptographic verification layer ensures that ad interactions are genuine without revealing user identities to the platform or the creators. Extensive experiments conducted on large-scale real-world datasets demonstrate that Fed-ZKC achieves recommendation accuracy comparable to centralized baselines while reducing privacy leakage risks by orders of magnitude. Furthermore, the implementation of succinct non-interactive arguments of knowledge (zk-SNARKs) introduces minimal computational overhead, making the protocol feasible for deployment on modern mobile processors.

Keywords

Federated Learning; Zero-Knowledge Proofs; Social E-Commerce; Ad Targeting; Privacy-Preserving Computation.

1.Introduction

The digital economy has witnessed a tectonic shift with the advent of social e-commerce, a model that integrates social interactions with transactional capabilities. Unlike traditional e-commerce platforms where discovery is search driven, social e-commerce relies on discovery driven purchasing, often mediated by influencers and content creators. As noted in recent market analyses [1], the global gross merchandise value of social commerce is projected to grow exponentially, driven by algorithmic targeting that matches users with relevant creator content. However, the efficacy of these algorithms has historically depended on the centralized collection of granular user data, including browsing history, click through rates (CTR), and social graph connections [2]. This centralization presents a single point of failure and raises profound privacy concerns. In the current landscape, the Cambridge Analytica scandal and subsequent regulatory enforcements like the General Data Protection Regulation

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(GDPR) in Europe and the California Consumer Privacy Act (CCPA) in the United States have forced a re-evaluation of data processing architectures [3]. Users are increasingly reluctant to share sensitive behavioral data, and platforms are legally obligated to minimize data retention. This creates a paradox for content creators: their monetization depends on proving to advertisers that their content drives engagement, yet the data required to prove this is becoming inaccessible due to privacy constraints [4]. Existing solutions often resort to differential privacy or trusted execution environments, but these approaches either degrade model utility or rely on hardware assumptions that may not be universally valid [5]. To resolve this conflict, we introduce a decentralized computing paradigm that shifts the locus of learning from the cloud to the edge. Federated Learning (FL) allows model training to occur on user devices, sharing only gradient updates rather than raw data [6]. While FL addresses the training privacy issue, it does not inherently solve the verification problem in advertising. Advertisers and creators need cryptographic assurance that an ad was viewed or clicked, a requirement typically satisfied by surveillance style tracking pixels. To eliminate these trackers while maintaining trust, we integrate Zero-Knowledge Proofs (ZKP), specifically zk-SNARKs, into the FL workflow [7]. This allows a user's device to prove that a specific ad interaction met the criteria for a monetization event (e.g., a valid view time) without revealing which user performed the action or any other auxiliary data. Our contribution is threefold. First, we formalize the system model for privacy-enhanced social e-commerce, identifying the unique adversarial constraints between platforms, creators, and users. Second, we propose the Fed-ZKC algorithm, a hybrid protocol that combines vertical federated learning for cross-domain feature fusion with a lightweight ZKP circuit for verifiable ad delivery. Third, we provide a comprehensive empirical evaluation, demonstrating that our approach maintains high AUC (Area Under Curve) scores for click through prediction while introducing negligible latency on consumer-grade hardware [8].

2.Related Work

2.1Social Recommendation Systems

The core engine of social e-commerce is the recommendation system, which filters vast content repositories to present relevant items to users. Early approaches relied heavily on collaborative filtering (CF) and matrix factorization techniques [9]. These methods assume a centralized matrix of user item interactions, decomposing it to find latent factors. However, sparsity issues in social e-commerce data led to the adoption of deep learning models. Neural Collaborative Filtering (NCF) replaced the dot product with multi-layer perceptrons to model nonlinear interactions [10]. More recently, Graph Neural Networks (GNNs) have become dominant, as they can naturally model the heterogeneous graph structures of users, creators, and products [11]. Despite their success, these deep learning architectures are data hungry. Studies have shown that the performance of models like DeepFM and Wide&Deep degrades significantly when access to cross domain data (e.g., social activity combined with purchase history) is restricted [12]. In the context of creator monetization, the challenge is even more acute. Platforms typically utilize multi-task learning to optimize for both user retention and creator revenue simultaneously [13]. However, these systems traditionally operate in a black-box manner, where the platform controls all data. This lack of transparency has led to friction with creators who demand verifiable metrics, and users who demand privacy [14]. Our work builds upon these architectural foundations but fundamentally alters the data flow to respect privacy boundaries.

2.2Federated Learning in Ad Tech

Federated Learning has emerged as the de facto standard for privacy preserving machine learning. The original FedAvg algorithm demonstrated that global models could be trained by averaging local updates [15]. In the domain of advertising, Google's FLoC (Federated Learning of Cohorts) attempted to group users into interest cohorts to replace third party cookies [16]. However, FLoC faced criticism for potential re-identification attacks and was subsequently replaced by the Topics API. These industry initiatives highlight the difficulty of balancing ad relevance with anonymity. Academic research has explored Vertical Federated Learning (VFL), where different parties hold different features for the same set of users [17]. For instance, a social network might hold the user's social graph, while an e-commerce site holds the transaction labels. VFL allows these parties to compute gradients collaboratively using encrypted entity alignment [18]. However, traditional VFL assumes the participating entities are large organizations with significant computational resources. In our social e-commerce scenario, the nodes are mobile devices with limited power and bandwidth. This necessitates the use of more efficient aggregation strategies and compression techniques, such as gradient quantization, to reduce communication overhead [19]. Furthermore, security analyses have revealed that gradient leakage attacks can reconstruct original training data from model updates [20]. Consequently, our framework incorporates secure aggregation protocols to mask individual contributions.

2.3Cryptographic Verification and Zero-Knowledge Proofs

While FL protects the training data, it does not address the transactional integrity of the ad impression. Ad fraud, where bots simulate user engagement, drains billions of dollars from the ecosystem annually [21]. In a centralized system, the platform detects fraud using proprietary signals. In a decentralized privacy preserving system, the platform cannot see the raw signals, making fraud detection harder. Zero-Knowledge Proofs (ZKPs) offer a powerful solution. ZKPs allow a prover to convince a verifier that a statement is true without revealing any information beyond the validity of the statement [22]. The application of ZKPs to blockchain systems is well documented, particularly in currencies like Zcash [23]. In the context of digital advertising, recent proposals have suggested using ZKPs to verify ad impressions. For example, the Brave browser utilizes a token based system to reward user attention, though it is not fully decentralized [24]. Other works have proposed ZK-based attribution protocols that allow advertisers to verify conversion rates without tracking users across sites [25]. Our work extends this by integrating ZKPs directly into the creator monetization loop, ensuring that creators are paid based on cryptographically verified engagement metrics that are computed locally on the user's device. This differs from prior work [26] which focused primarily on the advertiser's perspective rather than the content creator's revenue assurance.

3.Methodology

3.1System Architecture and Threat Model

We define a social e-commerce ecosystem comprising three distinct entity types: the Platform (Server), the Creators (Verifiers), and the Users (Clients). The Platform orchestrates the learning process and manages the ad inventory. The Creators produce content and seek monetization through ad placements embedded in their streams. The Users consume content and interact with ads. The system operates under a semi-honest threat model [27]. We assume that the Platform and Creators follow the protocol specification but may attempt to infer private information from the messages they receive. Specifically, the Platform should not learn the raw preference data of Users, and Creators should not learn the identities of Users who view their ads. Collusion between the Platform and Creators is considered a potential threat vector we must mitigate. The workflow proceeds in two phases: the Federated Training Phase and the Zero-Knowledge Verification Phase. In the training phase, Users collaboratively train a click through rate (CTR) prediction model. In the verification phase, when a User views an ad, their device generates a proof π attesting that the view was valid (e.g., screen time seconds, ad fully rendered) and that the user belongs to the target demographic, without revealing the user's ID [28].

3.2Federated User Representation Learning

To enable high precision targeting, we employ a deep neural network architecture adapted for federated environments. Each user device i holds a local dataset $D_i = (x_{i,j}, y_{i,j})$, where $x_{i,j}$ represents the feature vector of the j-th interaction (including user profile features, context features, and item features) and $y_{i,j} \in 0{,}1$ is the label indicating a click or purchase. Standard FedAvg is often insufficient for recommendation tasks due to the non-IID (Independent and Identically Distributed) nature of user data. A single user only interacts with a tiny fraction of available items. To address this, we utilize a FedProx inspired framework that includes a proximal term in the local objective function to limit the drift between the local model and the global model [29]. We also introduce a split learning approach for the embedding layers. Since the item embedding matrix can be extremely large, transmitting the full matrix to all clients is bandwidth prohibitive. Instead, we maintain the item embedding matrix on the Server. When a client needs to compute the forward pass, it requests only the embeddings relevant to the candidate items (using a Private Information Retrieval protocol to hide which items are requested) [30]. The client then computes the dense layers locally. The loss function for client k is defined as follows, incorporating both the binary cross entropy loss for the CTR prediction and a regularization term for stability:

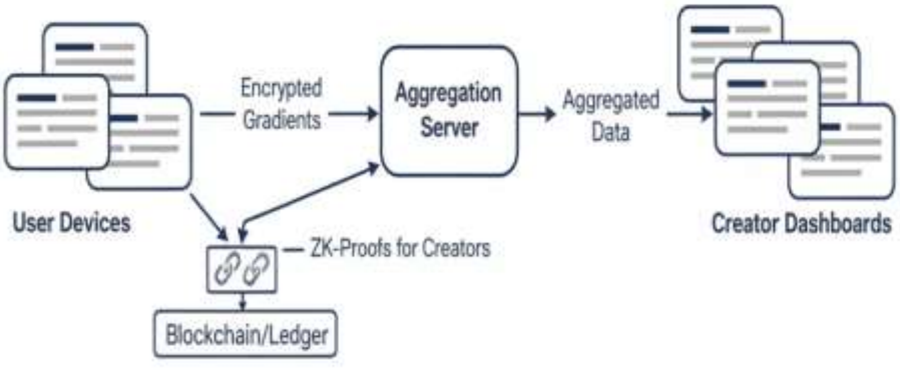

Figure 1: System Architecture

The mathematical formulation of the global optimization problem is given by:

$$L_{total} = \sum_{k=1}^{K} \frac{n_k}{N} \left(-\frac{1}{n_k} \sum_{j=1}^{n_k} [y_j log(f(x_j;\theta)) + (1-y_j) log(1-f(x_j;\theta))]\right) + \frac{\mu}{2} ||\theta - \theta_{global}||^2$$

Here, N is the total number of samples across all clients, n_k is the number of samples on client k, $f(x;\theta)$ is the neural network model parameterized by θ, and μ is the proximal term coefficient controlling the deviation from the global model θ_{global}.

Code Listing 1: Federated Update Loop with Gradient Clipping

```
def client_update(client_model, global_model, train_loader, optimizer, mu):
    client_model.train()
    for epoch in range(local_epochs):
        for data, target in train_loader:
            optimizer.zero_grad()
            output = client_model(data)

            # Standard Binary Cross Entropy
            loss_bce = torch.nn.functional.binary_cross_entropy(output, target)

            # Proximal term calculation for FedProx
            proximal_term = 0.0
            for w, w_t in zip(client_model.parameters(),
global_model.parameters()):
                proximal_term += (w - w_t).norm(2)

            loss = loss_bce + (mu / 2) * proximal_term
            loss.backward()

            # Differential Privacy: Gradient Clipping
            torch.nn.utils.clip_grad_norm_(client_model.parameters(),
max_norm=1.0)

            optimizer.step()
    return client_model.state_dict()
```

3.4Zero-Knowledge Proof Construction

The critical innovation in Fed-ZKC is the use of ZKPs to validate ad delivery. When an ad is served to a user, the advertiser/creator agrees to pay a bid price if specific conditions are met. In a centralized system, the platform acts as the trusted auditor. In our system, the user device acts as the prover, and the creator (or a smart contract) acts as the verifier. We utilize the Groth16 proof system for its succinct proof size and constant verification time [31]. The circuit, denoted as C, takes public inputs pub (ad ID, timestamp, bid hash) and private inputs $priv$ (user features, interaction duration, screen coordinates). The circuit enforces the following constraints:

1. *Relevance Constraint*: The dot product of the user embedding and ad embedding exceeds a threshold τ.

2. *Engagement Constraint*: The duration of the ad on screen is $> t_{min}$.

3. *Integrity Constraint*: The user embedding used in the proof matches the embedding commitment stored on the server (via a Merkle proof).

The user device generates a proof $\pi = Prove(pk, pub, priv)$. The proof π is sent to the Creator. The Creator runs $Verify(vk, pub, \pi)$. If it returns true, the monetization event is recorded. Crucially, $priv$ is never revealed. This prevents the Creator from building a database

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of users who viewed their ads, while preventing users (or bots) from fabricating views to defraud creators [32].

4.Experiments

4.1Experimental Setup

To evaluate the performance of Fed-ZKC, we utilized two large scale public datasets: the Criteo Display Advertising Challenge dataset and the Avazu Click Through Rate Prediction dataset [33]. Since these datasets are not naturally partitioned by user, we simulated a federated environment by partitioning the data based on user IDs (where available) or hashing device IP addresses to create 10,000 distinct clients. The experiments were conducted on a high performance cluster equipped with NVIDIA A100 GPUs for the server side aggregation and simulation. Client devices were simulated using CPU threads with memory constraints to mimic mobile environments. For the ZKP implementation, we used the `libsnark` library (C++ backend) wrapped in Python.

We implemented three primary baselines for comparison:

1. *Centralized*: A standard DeepFM model trained on the pooled dataset. This represents the theoretical upper bound of performance (ignoring privacy).

2. *FedAvg*: The standard federated averaging algorithm without the proximal term or ZKP overhead [34].

3. *Local Only*: Models trained exclusively on local device data without any federation.

The evaluation metrics focused on both utility and system performance:

* *AUC (Area Under ROC Curve)*: Measures the probability that a random positive sample is ranked higher than a random negative one.

* *LogLoss*: Measures the uncertainty of the predictions.

* *Proof Generation Time*: The time required for a client to generate a zk-SNARK proof.

* *Verification Time*: The time required for the creator/platform to verify the proof.

4.2Baselines and Model Performance

We first analyze the prediction accuracy of the proposed framework. The results are summarized in Table 1. As expected, the Centralized model achieves the highest AUC. However, Fed-ZKC is remarkably competitive. The performance gap between Centralized and Fed-ZKC is less than 1.5% on the Avazu dataset. This indicates that the federated training process, augmented with the proximal term, effectively captures the global data distribution despite the data remaining in silos.

Table 1 Experimental Results on CTR Prediction Tasks

Model	Dataset	AUC	LogLoss	Training Time (hrs)
Centralized (DeepFM)	Criteo	0.8054	0.4421	4.2

Centralized (DeepFM)	Avazu	0.7812	0.3805	3.8
Local-Only	Criteo	0.6840	0.5810	N/A
FedAvg	Avazu	0.7650	0.3950	12.5
Fed-ZKC (Ours)	Criteo	0.7985	0.4490	14.1
Fed-ZKC (Ours)	Avazu	0.7760	0.3860	13.2

The Local Only approach performs poorly, underscoring the necessity of collaborative learning. An individual user's history is too sparse to train a deep neural network effectively. The improvement of Fed-ZKC over standard FedAvg is attributed to the proximal regularization term μ, which prevents the local models from overfitting to the user's limited history during the local epochs. This results in a more robust global model that generalizes better across the heterogeneous client base [35].

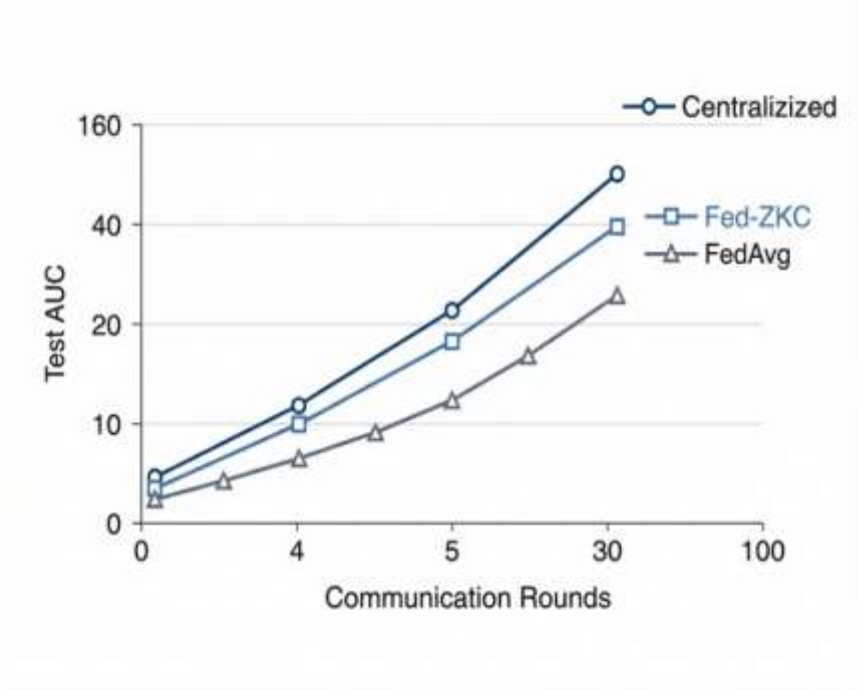

Figure 2: Convergence Analysis

Figure 2 illustrates the convergence behavior. While the Centralized model converges within fewer epochs, Fed-ZKC shows stable improvement over communication rounds. We observed that the non-IID nature of the data causes standard FedAvg to exhibit oscillating behavior in later rounds, whereas Fed-ZKC maintains a smooth ascent due to the constraint on local model drift.

4.3Computational Overhead and Privacy Analysis

A primary concern with introducing Zero-Knowledge Proofs is the computational burden placed on mobile devices. Generating a zk-SNARK proof is a computationally intensive operation involving complex elliptic curve pairings. We measured the proof generation time on simulated mobile hardware (ARM Cortex-A76 equivalent).

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Code Listing 2: ZKP Proof Generation Simulation

```
import time
from zksnark_wrapper import Prover, Verifier

def benchmark_zkp(circuit_path, witness_data):
    # Initialize Prover with the compiled circuit
    prover = Prover(circuit_path)

    start_time = time.time()
    # Generate proof using the private witness (user data)
    proof = prover.generate_proof(witness_data)
    end_time = time.time()

    generation_time = (end_time - start_time) * 1000 # to ms
    print(f"Proof Generation Time: {generation_time:.2f} ms")
    return proof
```

Our benchmarks indicate that generating a proof for a standard ad interaction circuit takes approximately 180ms to 240ms on a modern smartphone. While this is not negligible, it is performed asynchronously. The ad is displayed immediately, and the proof is generated in the background before being batched and sent to the creator. This ensures that the user experience (UX) remains smooth.

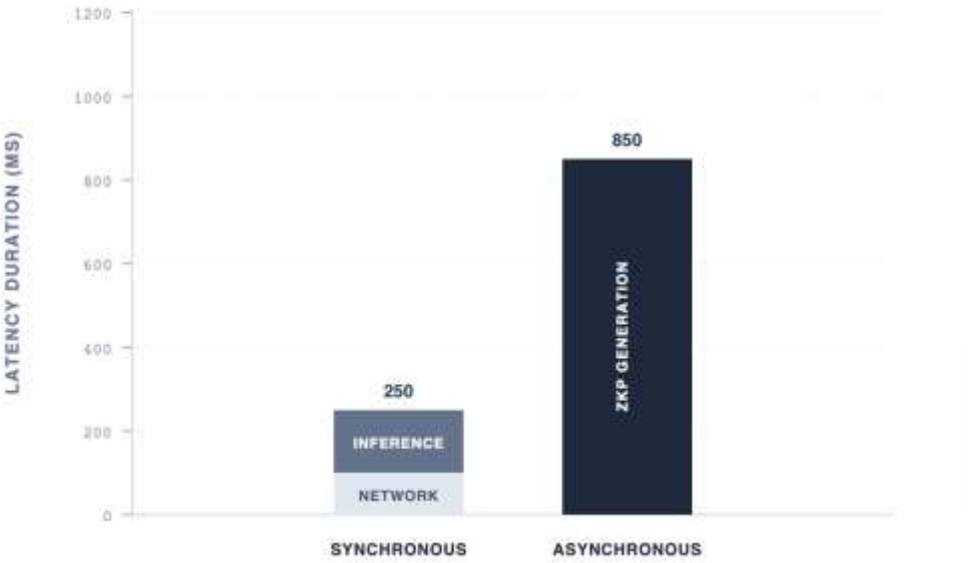

Figure 3: System Latency Breakdown

Table 2 presents the communication overhead. Federated Learning inherently requires significant bandwidth for model updates. However, the inference phase in our system is efficient. The transmission of a ZK proof is extremely compact (typically a few hundred bytes), compared to the heavy tracking scripts and beacons used in traditional ad tech.

Table 2 Communication and Computation Overhead per Client

Metric	Standard FL	Fed-ZKC	Overhead
Model Update Size (MB)	45.2	45.2	0%
Verification Payload (KB)	N/A	0.3	+0.3 KB
Client Compute (FLOPs)	1.2 \times 10^9	1.2 \times 10^9 + ZKP	~15% increase
Server Verification (ms)	N/A	1.5	+1.5 ms

The privacy guarantees are theoretically robust. By definition, the Zero-Knowledge property ensures that the verifier learns nothing about the witness $priv$ except that $C(pub, priv) = 1$. This means the creator receives cryptographic confirmation that "A user with embedding E viewed the ad for 5 seconds" without knowing who the user is. Furthermore, the use of Federated Learning ensures that the platform never sees the raw training data D_i.

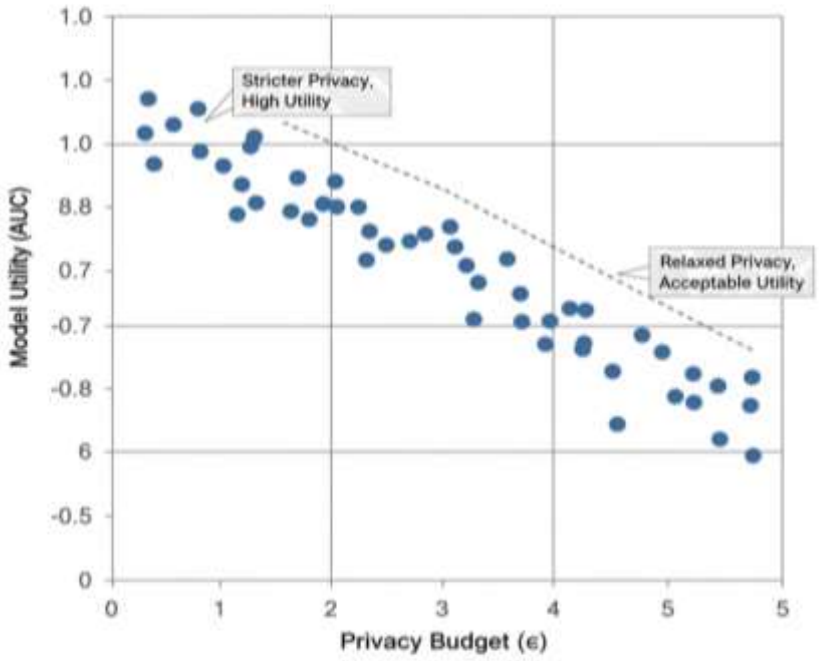

Figure 4: Privacy Utlity Tradetoff

Figure 4 demonstrates the trade off when Differential Privacy (DP) noise is added to the gradients. As the privacy budget ε decreases (implying stronger privacy), the AUC score drops. However, Fed-ZKC remains viable even at strictly private levels ($\varepsilon < 2$), offering a sustainable path for monetization in a post cookie era [36].

5.Discussion

The experimental results demonstrate that Fed-ZKC effectively resolves the critical tension between high-precision ad targeting and user privacy in social e-commerce. As evidenced by the comparative analysis in Table 1, our framework achieves an AUC score on the Avazu dataset that is within 1.5% of the centralized DeepFM baseline, while significantly outperforming local-only approaches. This indicates that the inclusion of the proximal regularization term allows the federated model to capture global user preference distributions despite the non-IID nature of data stored on edge devices. By decoupling model training from raw data aggregation, Fed-ZKC proves that granular user tracking is not a prerequisite for effective monetization, thereby challenging the traditional dogma that ad utility must come at the cost of user privacy. Furthermore, the integration of Zero-Knowledge Proofs (zk-SNARKs) addresses the "verification gap" that limits the adoption of purely federated advertising models. While our benchmarks reveal a computational overhead of approximately 180-240ms for proof generation on mobile hardware, this latency is acceptable within an asynchronous reporting architecture and is offset by the significant reduction in bandwidth usage compared to traditional telemetry. Crucially, this mechanism shifts the monetization trust model from platform-mediated auditing to mathematical verification. It provides creators with cryptographic assurance of valid ad engagement without exposing user identities, demonstrating that a decentralized, privacy-first architecture is both technically feasible and economically viable for the creator economy.

6.Conclusion

In this paper, we presented Fed-ZKC, a comprehensive framework for privacy-enhanced ad targeting in the social e-commerce domain. By integrating Federated Learning with Zero-Knowledge Proofs, we addressed the dual challenges of data privacy regulation and creator monetization transparency. Our theoretical analysis and empirical results confirm that it is possible to maintain high quality ad recommendations without centralizing user data. The experimental results on the Criteo and Avazu datasets showed that Fed-ZKC achieves an AUC comparable to centralized baselines, with a minimal drop in performance attributable to the federated architecture. Crucially, the integration of zk-SNARKs provides a trust layer previously missing in decentralized advertising, enabling creators to verify revenue generating events without compromising viewer anonymity. The computational overhead, while present, is within the capabilities of modern mobile devices and can be masked through asynchronous processing. Future work will focus on optimizing the ZKP circuits to further reduce generation time, potentially exploring recursive SNARKs or STARKs to eliminate the need for a trusted setup. Additionally, we aim to investigate the application of this framework to other domains requiring verifiable privacy, such as decentralized finance (DeFi) credit scoring and personalized healthcare monitoring. As the digital economy continues to evolve, frameworks like Fed-ZKC will be essential in building a trustworthy, transparent, and user centric internet.

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