FLea Market Whitepaper

Balkeum Labs

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Abstract

Federated Learning (FL) enables collaborative model training without sharing raw data, preserving privacy across organizations. FLea Market enhances traditional FL by integrating Secure Multi-Party Computation (SMPC) for secure gradient aggregation and privacy.

FLea Market's core innovation lies in its decentralized governance and tokenomics framework, using SubDAOs to incentivize high-quality data contributions and ensure accountability. Token-based incentives align participant contributions with ecosystem success, while governance tokens empower stakeholders to influence key decisions. End-users pay usage fee for FL models per inference, without the need to pay for the whole model gradients.

By combining SMPC, DAOs, and tokenomics, FLea Market offers a scalable, privacy-preserving solution for decentralized AI development.

1 Introduction

1.1 Federated Learning in Privacy-Enhancing Technologies

The rapid advancement of artificial intelligence (AI) is driven by access to extensive datasets, but privacy concerns and regulatory restrictions often keep data siloed across organizations, hindering collaboration. Privacy-Enhancing Technologies (PETs) aim to address this challenge, and Federated Learning (FL) has emerged as a key PET for collaborative model training without compromising data privacy. FL allows multiple parties to train a shared global model by exchanging model updates instead of raw data, ensuring that sensitive information remains local.

Compared to other PETs like Fully Homomorphic Encryption (FHE) and Differential Privacy (DP), FL offers a more practical and efficient solution. While FHE is computationally expensive and DP can reduce model accuracy, FL combined with Secure Multi-Party Computation (SMPC) provides effective privacy protection and decentralized model training. FLea Market builds on these principles by integrating SMPC for secure gradient aggregation, ensuring that individual participants' gradients remain confidential even during the collaborative update process, making it a scalable solution for privacy-preserving collaborative learning.

1.2 The Need for Incentivized Federated Learning and Governance

Despite its advantages, traditional FL systems face challenges in participant engagement and data quality. Without proper incentives, organizations may be reluctant to contribute their data or computational resources, leading to suboptimal model performance. Additionally, there's a risk of participants providing low-quality or even malicious data, which can corrupt the global model.

An incentivized FL platform with a robust governance structure is essential to address these challenges. By introducing token-based incentives and decentralized governance through SubDAOs (Sub Decentralized Autonomous Organizations), participants are motivated to contribute high-quality data and actively engage in the training process. External validators or peer reviewers are rewarded with tokens for ensuring the integrity and accuracy of model updates. This governance model not only fosters collaboration and trust among participants but also enhances the overall performance and reliability of the federated learning system.

2 FLea Market Pipeline Overview

The FLea Market pipeline is structured into multiple stages, each designed to ensure privacy, security, and effective participant incentives. Below is an overview of the entire process from training to inference:

1. **Local Training**: Each organization trains its model locally on private data, ensuring plaintext data never leaves the premise. SMPC is used to secret-share gradients, maintaining data confidentiality.

2. **Peer Validation**: Participants validate each other's model updates using secure 2PC (Garbled Circuits) to ensure data quality. External validators rank contributions, with top-ranked participants receiving higher rewards, motivating high-quality data sharing.

3. **Secure Gradient Aggregation**: Gradients are securely aggregated using SMPC. This ensures that no individual gradient is exposed during aggregation, and all computations occur on encrypted data.

4. **Global Model Update**: The aggregated gradients are used to update the global model. Governance tokens allow participants to vote on model updates, fostering transparency and community-driven decision-making.

5. **Token Incentives and SubDAO Governance**: Participants receive platform tokens as rewards, while SubDAO-specific governance tokens are

distributed to contributors. These governance tokens are soul-bound, tied to active contributions, and revoked upon exit; for internal use only.

6. **Secure Inference**: The updated global model is available for inference. The model itself remains hidden from all participants. Input data from end users is secret-shared using PETs, ensuring data privacy. Inference is performed on encrypted inputs, and results are securely returned to users.
7. **Pay-per-inference**: The inference process follows a pay-per-inference model, where users pay in platform tokens for each inference request. These are instantly distributed among contributors of the SubDAO in proportion to their ranking as previously determined during the peer validation phase.
8. **Lifecycle and Redistribution**: At the end of each federated learning cycle, SubDAO governance tokens are redistributed based on new contributions, ensuring ongoing engagement and sustainability.

3 Federated Learning

Federated Learning (FL) is a decentralized approach to machine learning where multiple clients collaboratively train a model without sharing their raw data. This preserves privacy, as data remains on each client device, and only model updates are shared with a central server for aggregation [1]. The goal is to minimize privacy risks while enabling the collective use of distributed data for model improvement [4].

3.1 Model Training in Federated Learning

In a typical federated learning setting, there are K clients, each holding a local dataset $\mathcal{D}_k = \{(x_i, y_i)\}_{i=1}^{n_k}$, where x_i represents the input features and y_i represents the corresponding labels. Each client aims to collaboratively train a global model $w \in \mathbb{R}^d$ (with d being the dimension of the model's parameters) without sharing their private dataset [2].

Each client k solves the following optimization problem locally:

$$\min_w F_k(w) = \frac{1}{n_k} \sum_{i=1}^{n_k} \ell(w; x_i, y_i)$$

where $\ell(w; x_i, y_i)$ is the loss function for the model w on the data point (x_i, y_i), and n_k is the number of data points at client k [3]. The global objective is to minimize the weighted average of these local objectives:

$$\min_w F(w) = \sum_{k=1}^{K} \frac{n_k}{n} F_k(w)$$

where $n = \sum_{k=1}^{K} n_k$ is the total number of data points across all clients [1].

3.2 Federated Averaging Algorithm

The most common algorithm used in federated learning is Federated Averaging (FedAvg) [1]. This algorithm works as follows:

1. Each client k initializes the model parameters $w_k^{(0)}$. 2. In each communication round t, the server sends the current global model $w^{(t)}$ to all clients. 3. Each client updates the model locally by solving the optimization problem using gradient descent or another optimization method:

$$w_k^{(t+1)} = w_k^{(t)} - \eta \nabla F_k(w_k^{(t)})$$

where η is the learning rate and $\nabla F_k(w_k^{(t)})$ is the gradient of the local loss function [3].

4. After the local updates, each client sends its updated model parameters $w_k^{(t+1)}$ back to the central server. 5. The server aggregates the updates from the clients to form the new global model:

$$w^{(t+1)} = \sum_{k=1}^{K} \frac{n_k}{n} w_k^{(t+1)}$$

This process is repeated for several rounds until the global model converges [1].

3.3 Privacy in Federated Learning

One of the core motivations behind federated learning is to ensure that data privacy is maintained. Unlike traditional machine learning approaches where data is centralized, federated learning keeps the data decentralized and only transmits model updates. However, the model updates themselves can still leak information about the underlying data (gradient leakage), leading to the need for additional privacy-preserving mechanisms, such as secure multi-party computation (SMPC), as will be explained below.

4 Private Blockchain SMPC Solution

The Private Blockchain SMPC solution is integrated into the FLea Market platform to enhance the efficiency, scalability, and security of federated learning. In this section, we outline how Secure Multi-Party Computation (SMPC) is used in our federated learning pipeline, providing detailed descriptions of each stage of the process.

4.1 Federated Learning Pipeline with SMPC

4.1.1 Model Training On-Premise

Each member trains a local model on its private data using on-premise hardware resources such as GPU clusters. After the local training phase, each member obtains gradients, which must remain confidential to prevent gradient leakage. Instead of sharing these raw gradients, SMPC is used to securely share and aggregate these values [4].

4.1.2 Pairwise Peer Validation Using 2PC (Garbled Circuits)

After training, each member's weights are validated externally with each other's data using a Two-Party Computation (2PC) approach. Specifically, the Garbled Circuits protocol is used to ensure pairwise peer validation while keeping both the model weights and the input data confidential.

Let w_i be the weights from member i and x_j be the data from member j. In 2PC, member i and member j collaborate to validate w_i against x_j without revealing their respective data. The process involves the following steps:

1. Member i creates a garbled circuit that represents the validation function $f(w_i, x_j)$, which evaluates the model weights against the peer's data. 2. Member j receives the garbled circuit and encrypted input labels, which they use to evaluate the function without learning anything about w_i. 3. The output of the function is shared between both members to confirm the validation result without revealing any underlying data.

The garbled circuit ensures that neither w_i nor x_j is disclosed during the validation process. This approach allows each member to validate the accuracy and reliability of another member's model weights while maintaining complete data confidentiality [7].

Mathematically, let $f(w_i, x_j)$ represent the validation function. The result y_{ij} of the pairwise validation is computed as:

$$y_{ij} = f(w_i, x_j),$$

where $f(\cdot)$ is computed using garbled circuits to maintain privacy. This ensures that each pairwise validation step is secure and does not expose any sensitive information.

4.1.3 Secure Gradient Aggregation

The decentralized nodes perform secure multi-party computation to aggregate the validated gradients from all participating members. The aggregation is carried out in a non-interactive manner, reducing communication overhead while maintaining data privacy [7]. Specifically, each node performs computations on the shares it possesses, and the aggregated gradients G_{agg} are computed as:

$$G_{agg} = \sum_{i=1}^{K} w_i,$$

where K is the number of participating members. This method ensures that none of the nodes or members can reconstruct the original gradients, as only the final aggregated gradients are securely output [8].

4.1.4 Securing Final Aggregated Gradients

The final aggregated gradients are kept secure using the SMPC protocol, ensuring that they remain inaccessible to unauthorized entities. These gradients are then used for inference, and access is provided only through privacy-preserving channels that prevent unauthorized viewing [9].

4.1.5 Inference Requests from End Users

When an end user, such as a patient's wearable device or a healthcare provider, requests an inference, the input data is secret-shared and masked using the preprocessing phase of the SMPC protocol. This ensures that the input data remains fully confidential throughout the inference process, with no party in the network, including nodes or members, having access to the unmasked input [10].

Let x be the input data from the end user. Using LSSS, x is split into n shares, $x_1, x_2, \ldots, x_n$, such that:

$$x = \sum_{j=1}^{n} \lambda_j x_j,$$

where λ_j are random coefficients. These shares are distributed across the nodes for secure inference.

4.1.6 Secure Inference Using SMPC

The secret-shared aggregated gradients and secret-shared input data are combined using SMPC. The decentralized network of nodes performs secure inference on the masked data using non-interactive SMPC, which eliminates the need for multiple communication rounds [11]. The inference result y is computed as:

$$y = f(G_{agg}, x),$$

where $f(\cdot)$ represents the inference function applied to the aggregated gradients and input data. This process ensures that inference is both fast and privacy-preserving [12].

4.1.7 Returning Inference Results

The inference results are returned to the requesting party in an encrypted or masked form. Only the intended recipient can decrypt and view the results, ensuring that neither the members nor the nodes have access to the final output. This guarantees that the entire process, from training to inference, remains private and secure [13].

4.2 Key Benefits of Using SMPC

- **Privacy-Preserving Validation and Secure Aggregation:** SMPC enables privacy-preserving peer validation and secure aggregation of gradients using protocols like 2PC and garbled circuits, ensuring that no single entity can access the complete data or model weights [7, 8].

- **Scalability and Efficiency:** The non-interactive nature of SMPC reduces communication overhead, making it highly scalable and efficient for large numbers of participants, suitable for large-scale federated learning scenarios [15, 18].

- **End-to-End Security and Confidential Inference:** SMPC ensures confidentiality of both input data and inference results, offering end-to-end protection against data leakage throughout the federated learning pipeline [10, 17].

- **Decentralization and Robustness:** The decentralized structure of the SMPC system, particularly in blockchain-based solutions, eliminates single points of failure and reduces the risks associated with centralized data breaches [16].

5 Public Blockchain SMPC Solution

The Public Blockchain SMPC solution leverages Nillion's unique decentralized technology to enhance federated learning on the FLea Market platform. Unlike the private blockchain-based SMPC approach, which relies on SubDAO-wide compute, Nillion's system relies on a broader, more decentralized architecture that removes the need for direct peer-to-peer interactions. This section highlights the key differences and advantages of using Nillion's public blockchain approach over the private solution [29].

5.1 Key Differences in Nillion's SMPC Implementation

5.1.1 Decentralized Node Architecture

Instead of relying on SubDAO-wide computations, Nillion's public blockchain spreads computation across a wide, decentralized network of nodes. This ensures that no single entity controls the flow of data or computations, improving privacy and removing single points of failure [29].

5.1.2 NMC for Data Splitting and Distribution

Nillion uses its proprietary Nil Message Compute (NMC) protocol, which securely splits data across nodes without requiring private or encrypted communication. This allows for faster and more scalable operations compared to traditional secret-sharing methods, which often involve higher communication overhead [29].

5.1.3 Trustless Validation and Aggregation

The validation and aggregation process in Nillion's system is conducted entirely by its decentralized network. Rather than relying on pairwise peer validation (e.g., garbled circuits or Two-Party Computation), Nillion's nodes handle the validation across the network, providing trustless and distributed peer validation. This allows for greater scalability and security without the need for complex, interactive protocols between federated learning members [29, 30].

5.1.4 Non-Interactive, Large-Scale Gradient Aggregation

While private blockchain solutions require interactive exchanges to aggregate gradients, Nillion's SMPC eliminates this requirement. Its non-interactive, trustless aggregation process ensures that gradients can be securely aggregated across a large number of participants without the need for direct communication between nodes or members. This improves scalability and reduces computational and communication overhead [31].

5.1.5 Decentralized Inference and Data Security

Inference requests are handled using Nillion's decentralized nodes, further enhancing privacy and security. No single party holds complete access to the data or the aggregated model. With many more nodes outside of the SubDAO, collusion among members is now rendered meaningless. The end-to-end decentralization makes the system inherently more resistant to breaches and data reconstruction attacks [29].

5.2 Key Benefits of Nillion

- **Higher Decentralization:** Computations are distributed across a larger network of nodes, improving security by removing central control or direct peer-to-peer interactions.
- **Scalable and Trustless Operations:** Nillion's infrastructure allows for non-interactive, trustless validation and aggregation, improving scalability without sacrificing privacy or efficiency.
- **No Private Communications:** The NMC technique avoids the need for encrypted channels, reducing communication costs while maintaining data confidentiality across a decentralized network.
- **Robust Against Single Points of Failure:** The system is more resilient to attacks and data breaches due to the full decentralization of both gradient aggregation and inference.
- **Efficient and Secure Inference:** By leveraging a distributed network for inference, Nillion ensures that inference remains fast, secure, and privacy-preserving, even for large-scale deployments.

6 Governance and Incentives Model for FLea Market

The governance model of FLea Market has been designed to ensure decentralized, transparent, and effective decision-making across the federated learning ecosystem. The governance structure revolves around the use of the platform token as the core utility for governance, rewards, and transactions. This section provides an overview of the governance and incentives framework.

6.1 Platform Token Governance

The entire FLea Market ecosystem is governed by the platform token, which serves as the foundation for governance decisions, rewards distribution, and payment for inference usage. The platform token ensures alignment of interests across the platform and provides a unified governance approach.

6.1.1 Platform Token for Governance

The platform token plays a central role in the governance of the FLea Market platform. Token holders can propose and vote on decisions that affect the entire ecosystem. The platform token holders can decide the fee rates to be applied when inference is paid for by non-SubDAO and SubDAO entities.

Key Governance Mechanisms:

- **Voting Rights:** Platform token holders participate in votes related to ecosystem-wide decisions. Proposals include adjusting fee rates for inference usage.
- **SubDAO Creation:** When a new SubDAO is created, participants invest platform tokens. In return, they receive soul-bound SubDAO governance tokens, which are non-transferable and revoked upon exiting the SubDAO [21].
- **Fee Rate Determination:** Platform token holders determine the fee rate for inference usage by non-SubDAO members, ensuring that value is accrued to the overall ecosystem.

6.2 SubDAO Governance

Each SubDAO operates autonomously within the FLea Market ecosystem, managing specific federated learning models and having its own internal governance mechanisms [2].

6.2.1 Soul-Bound Governance Tokens

Each SubDAO issues its own soul-bound governance tokens upon creation, distributed in proportion to the amount of platform tokens invested. These tokens cannot be traded or transferred and are revoked when the participant exits the SubDAO. When new entrants join the SubDAO in the next federated learning cycle, the SubDAO tokens are redistributed based on the new investment proportions [22]. This ensures that governance power is directly tied to active participants with a vested interest in the SubDAO's success.

Internal Decision-Making:

- **Voting on Model Parameters:** Members of each SubDAO use their governance tokens to vote on decisions related to model parameters, hyperparameters, data formats, and standards [1].
- **Contributor Rewards:** Rewards are distributed to SubDAO members based on their contributions, such as providing high-quality data, performing model validation, or enhancing model accuracy.
- **Revoking Tokens on Exit:** When a participant decides to exit a SubDAO, their governance tokens are revoked, ensuring that only active participants have governance rights [23].

6.3 Incentives and Reward Mechanism

The incentives within the FLea Market ecosystem are designed to reward participants for their contributions to federated learning models, encouraging high-quality data contributions, model validation, and sustained engagement.

6.3.1 Platform Token Rewards

Participants contributing to SubDAOs—whether by providing data, computational resources, or validation—are rewarded in platform tokens. These rewards incentivize participants to contribute high-quality work, as the amount of reward is tied to the quality and significance of their contributions [24].

Reward Distribution:

- **Data and Compute Contributions:** Contributors providing data and compute resources in the form of uploading gradients are rewarded in proportion to the quality of their data (*i.e* model update) [25]. This quality is determined by the averaged metric posted by peer validators who "review" the model updates against their own data (securely using Nilliion).
- **Peer validation:** Peer validators are also rewarded for their compute per external validation performed. The amount rewarded is constant per validation as previously determined by the SubDAO in relation to the reward pool (*i.e* the SubDAO treasury created by the investment pool).

6.3.2 Inference Usage Payments

Inference usage is divided into two parts: SubDAO members and non-SubDAO members.

Inference for SubDAO Members:

- The price of inference for SubDAO members is equivalent to the total rewards received by the top reward earner, meaning that the top earner can use the model for free, save computation costs on Nillion and a small fee charged by the platform (*i.e* SuperDAO, FLea Market) [26].
- Subsequent members must pay slightly more based on their rank, with a small cut (fee) taken by the platform for these inferences. The fee rate is determined by the SuperDAO.

Inference for Non-SubDAO Members:

- Non-SubDAO members must pay a higher price for inference, as determined by the SubDAO. A higher cut is also taken by the platform, with the fee rate determined by the SuperDAO [4].
- All inference payments are made using platform tokens, ensuring that value flows back into the ecosystem.

6.4 SubDAO Lifecycle and Governance Token Management

The lifecycle of each SubDAO in the FLea Market ecosystem involves several key stages: creation, operation, exit, and renewal. The governance and incentive mechanisms are designed to maintain an active and engaged participant base throughout the lifecycle.

6.4.1 Creation and Operation of SubDAOs

A new SubDAO is created when participants invest platform tokens. The invested tokens are used as rewards for contributions made within the SubDAO, distributed according to the quality of the training and validation efforts. Upon creation, governance tokens are issued proportionally to the participants based on their investment [27].

During the operational phase, SubDAO members contribute to the federated learning model through data provision, model training, and validation. They participate in governance by voting on model updates, parameter adjustments, data standards, and reward distributions. Contributors earn rewards in platform tokens based on their active participation and contribution quality.

6.4.2 Exit, Revocation, and Redistribution of Governance Tokens

When a participant chooses to exit a SubDAO, their governance tokens are revoked rather than burned. At the end of each federated learning cycle, governance tokens from all members—including those revoked by exiters—are collected and redistributed in proportion to new investments. This is achieved through a smart contract mechanism that reissues tokens based on fresh investment amounts while deactivating the previously held tokens [28].

Key Considerations:

- **Identity-Linked Tokens:** Since soul-bound tokens are tied to an identity (such as a participant's wallet address), the smart contract retains information about participants even if their tokens are revoked. This ensures continuity for participants who wish to reinvest in subsequent cycles.
- **Inactive vs. Active Tokens:** Instead of complete destruction, governance tokens are toggled between active and inactive states, allowing more flexibility in managing governance rights without full token reissuance.

7 Request-for-Model

The FLea Market ecosystem allows end users to request the creation of custom machine learning models tailored to their specific needs. This process, referred to as the "Request-for-Model" (RFM), enables inference requesters to directly influence the development of new models that are optimized for their particular requirements, while also suggesting an appropriate price for the inference cost.

7.1 Request Submission and Specification

End users can submit a Request-for-Model through the FLea Market platform by specifying the details of the desired model. This includes:

1. **Model Features and Parameters:** The requester defines specific features or parameters that the model should include. This might involve specifying certain types of input data, particular methods for feature extraction, or the type of prediction the model is intended to make.
2. **Intended Use Case:** The requester provides a description of the use case, detailing the context in which the model will be deployed and the expected outcomes.
3. **Performance Metrics:** The requester can specify the desired performance metrics, such as accuracy, sensitivity, specificity, or other domain-relevant metrics, to ensure the model meets their operational requirements.
4. **Budget:** The requester suggests a price they will pay per inference.

7.2 Community Engagement and Voting

Once a Request for Model (RFM) is submitted, it becomes available for review by the entire FLea Market community. Community members can contribute by adding comments to suggest revisions to the proposed specifications. These comments can be upvoted by others to highlight valuable insights or necessary changes. Interested entities may indicate their willingness to participate in the SubDAO if the RFM is approved. The submitter of the RFM, who will be the future inference requester, gives final approval for the formation of the SubDAO based on both community interest and the finalized specifications. Subsequently, a SubDAO is established for the model, and a crowdfunding period is initiated. The duration of the crowdfunding period is determined by the SuperDAO, unless otherwise specified by the RFM submitter.

8 Use Case: Pharmaceutical Company and Hospitals

Pharmaceutical companies can leverage the FLea Market platform to develop sophisticated models that serve their business and research needs. One such example is when a pharma company initiates a Request-for-Model (RFM) to create models such as market segmentation and sizing, treatment response prediction, or Health Economics and Outcomes Research (HEOR) analysis. This section provides an overview of how the FLea Market ecosystem can be used to fulfill such requests using real-world evidence (RWE) data from hospitals.

8.1 Request-for-Model by Pharma Company

A pharmaceutical company submits an RFM on the FLea Market platform, specifying the need for a machine learning model that can address a specific research or business goal. For instance, the pharma company may request a:

- **Market Segmentation and Sizing Model**: A model to segment patient populations based on specific clinical attributes and estimate the size of potential markets for a new drug.
- **Treatment Response Model**: A predictive model to identify which subsets of patients are likely to respond positively to a given treatment, based on past treatment outcomes and clinical characteristics.
- **HEOR Model**: A Health Economics and Outcomes Research (HEOR) model to evaluate the clinical and economic impact of treatments, using metrics such as quality-adjusted life years (QALYs) and healthcare costs.

The RFM includes specifications for the type of input data needed, the intended use case, desired performance metrics (such as accuracy, sensitivity, and specificity), and a proposed budget for the model's development.

8.2 Participation by Hospitals through SubDAO

Once the RFM is submitted, hospitals with access to relevant real-world evidence (RWE) data express interest in participating by joining a newly formed SubDAO. Participating hospitals contribute their data through a federated learning process, ensuring that sensitive patient information is never shared beyond their premises. The data typically includes Electronic Health Records (EHR) and Electronic Medical Records (EMR) that capture a broad range of clinical variables, treatment histories, and patient outcomes.

8.3 Model Development Using the FLea Market Pipeline

The development of the model is conducted through the FLea Market pipeline, which ensures privacy, security, and effective incentivization for all participants:

1. **Local Model Training**: Each participating hospital uses its EHR and EMR data to locally train a machine learning model according to the specifications provided by the pharma company. The data remains on-premise, and only model updates (i.e., gradients) are shared.

2. **Secure Gradient Aggregation**: Gradients from each hospital are securely aggregated using Secure Multi-Party Computation (SMPC) techniques to protect the privacy of individual hospitals' data. This aggregation step creates an updated global model without exposing any raw data.

3. **Peer Validation**: Validators within the SubDAO assess the quality of each hospital's model updates to ensure that only high-quality contributions are incorporated into the global model. Hospitals are ranked based on the quality of their contributions, with top performers receiving higher rewards.

4. **Global Model Update**: The securely aggregated gradients are used to update the global model iteratively. The pharma company, as the RFM submitter, is given visibility into model progress and can provide feedback or request adjustments as needed.

5. **Incentives and Rewards**: Participating hospitals receive platform tokens based on their contributions, with rewards linked to data quality and model improvements. Validators are also rewarded for ensuring the integrity and quality of the model.

8.4 Pay-per-Inference and Long-term Value

The pay-per-inference approach is significantly more cost-effective compared to purchasing entire anonymized datasets from hospitals, as it allows end-users to pay only for what they use. Revenue generated from these inference requests is distributed among the participating hospitals in proportion to their contributions, ensuring fair compensation.

This pay-per-inference model supports the ongoing lifecycle of the SubDAO and the federated learning model by encouraging new federated learning cycles with updated RWE data. It provides continuous incentives for participating hospitals and end-users who wish to utilize the most recent version of the model.

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