Ownership Tokenization and Incentive Design for Learning-based User-Generated Content

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***Abstract*—The Metaverse is established by twining a practical world in a virtual form, where users could become creators of learning-based user-generated content (UGC). However, the digital assets are not owned by the creators, which deviates from the decentralized Metaverse based on blockchain in Web 3.0. The contribution incentive design for UGC still faces the challenges of ownership verification and privacy protection. To this end, we propose minting the learning model into the non-fungible token (NFT) with federated learning (FL) assistance (referred to as FL-NFT), such that users as stakeholders can control the ownership and share the economic value of UGC. Specifically, the users are encouraged to establish a decentralized autonomous organization (DAO) to aggregate local models and mint FL-NFT. We formulate an auction interaction of FL-NFT as imperfect information Stackelberg game (IISG) to optimize the bidding strategies to realize individual rationality. Finally, we conduct simulations to show the effectiveness of the proposed scheme.**

***Index Terms*—Metaverse, blockchain, federated learning, NFT, UGC, incentive mechanism, Stackelberg game**

I. Introduction

The rapid development of emerging communication and multimedia, such as beyond 5G/6G, augmented reality (AR), virtual reality (VR) and mixed reality (MR), makes it possible for users to physically immerse in Metaverse [1]. In 1992, the word ”Metaverse” first appeared in the science fiction *Snow Crash* of Neal Stephenson [2]. In 2021, Facebook was even rebranded as ”Meta”, which brought the Metaverse back to cutting-edge discussions. Metaverse users (MUs) immerse in the virtual world built by Metaverse service providers (MSPs). Many technology giants, including Microsoft, Apple, Google, Tencent, Baidu, etc., have undertaken Metaverse services. Although increasingly Metaverse applications are emerging, it is still far from the ultimate version with the feature of immersion, embodiment, universality, and interoperability [3].

In Web 3.0, a decentralized virtual world will be constructed based on blockchain infrastructure. In order to support immersive experiences, massive learning-based UGCs are created. However, the creators cannot own digital assets due to monopolists and dictators. Autonomous ecosystems based on blockchain bring a feasible solution to address this critical issue. As a distributed ledger technology, blockchain can record the ownership of UGC in a decentralized manner. MUs, as essential stakeholders, can benefit from their contribution to the UGC. Meanwhile, the contribution incentive design for UGC is exposed to the risk of privacy disclosure.

Federated learning (FL) [4] is a privacy-preserving collaborative machine learning paradigm [5], which can be used to organize MUs to facilitate the creation of UGC in the form of an FL global model. In the FL training task, obtaining a high-quality model requires all participants to perform intensive computation through collective efforts. For example, MUs have to consume CPU, storage resources to train local models. A few incentive mechanisms for FL have been proposed, but they are not directly applicable in the Metaverse due to the immersion experience. In this paper, we are interested in an incentive mechanism to encourage MUs to participate in a decentralized autonomous organization (i.e., MU-DAO) to mint FL-NFT. The critical challenges are faced as follows:

C1. How to manage and control the trading of FL-NFT with the consensus of multiple stakeholders ?

C2. How to trade off the cost and benefit of MUs in the process of FL-NFT minting?

To mitigate the above challenges, we design an incentive mechanism to encourage MUs to establish a decentralized autonomous organization MU-DAO, which tokenizes the ownership of learning-based UGC by minting models to NFT. The novel contributions of this paper are listed as follows:

- To the best of our knowledge, we are the first to propose the idea of minting the learning models into NFT with FL assistance (i.e., FL-NFT). In order to mitigate the issue of monopolists and dictators, MUs are encouraged to establish an MU-DAO to train the FL models collaboratively.

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- We formulate an auction interaction of FL-NFT as imperfect information Stackelberg game (IISG) to optimize the strategies of MUs and MSPs, which realizes utility maximization and individual rationality. We adopt backward induction to derive the equilibrium solution.
- We conduct extensive numerical simulations based on real image datasets to validate the efficacy and efficiency of the proposed auction mechanism. Compared with benchmarks, our scheme can increase the quality of FL-NFT and achieve individual rationality.

The remainder of this paper is organized as follows. In Section II, we review related works. In Section III, the FL-NFT auction model and FL cost-benefit framework are presented. In Section IV, the strategies optimization of MUs and MSPs based on the IISG is given. We conduct simulations in Section V. Finally, we conclude the paper in Section VI.

II. Related Work

Recently, some researchers have focused on the study of incentive mechanisms designed for Metaverse. Xu et al. [6] designed a deep reinforcement learning (DRL)-based incentive mechanism for VR service in the wireless edge computation empowered Metaverse, in which a double Dutch auction mechanism is adopted to determine bidding strategies and allocation schemes of VR service. Jiang et al. [7] adopted Coded Distributed Computing (CDC) scheme to support rendering computation in Metaverse services, where coalition game and Stackelberg game were adopted to choose reliable workers to participate in the rendering tasks of Metaverse service. Sun et al. [8] investigated dynamic digital twin (DT) and two-stage Stackelberg game to encourage users to participate in aerial-assisted Internet of Vehicles (IoV). Lin et al. [9] proposed an incentive-based congestion control scheme for Digital Twin Edge Networks (DTENs), in which the Lyapunov optimization theory [10] was adopted to decompose the long-term control decision into a series of online associate decisions.

Blockchain is an essential infrastructure for the decentralized Metaverse ecosystem [3], that ensures security management and record for UGC with properties of decentralization, tamper-proof, trustworthiness, etc. A review [11] discussed the Metaverse based on blockchain from the technical point of view and puts forward some promising directions to innovate the usage of blockchain in Metaverse applications. Yang et al. [12] discussed how blockchain empowered artificial intelligence (AI) technologies in the three-dimensional (3D) virtual worlds. Fan et al. [13] implemented a blockchain-based prototype to simulate a decentralized, fair and transparent UGC trading platform, in which a dynamic game is adopted to model interactions among the mobile devices. Suhail et al. [14] proposed the usage of blockchain to target key challenges of untrustworthy data transmission and fault diagnosis in DT systems. However, there are few study on the incentive mechanisms in the blockchain-driven Metaverse.

FL as a collaborative distributed learning paradigm allows clients to share information by gradient parameters of models instead of raw data [3], which efficiently assists in executing intensive computation on many edge devices of MUs. Chen et al. [15] designed a collaborating mobile edge computing paradigm with FL for AR applications. In terms of FL model utility, Zhang et al. [16] focused on trading off the privacy cost and utility loss to maintain a provable privacy guarantee, and the results showed that there is no free lunch for the privacy-utility trade-off. To address the risk of free-riding and unfairness, FedIPR [17] verified the ownership of FL models by watermarks embedded into the model. Moreover, the existing works fail to address how to trade off the cost and utility of FL model training and determine the economic value of the FL models. Therefore, FL model market equilibria and incentive mechanism need to be investigated in-depth.

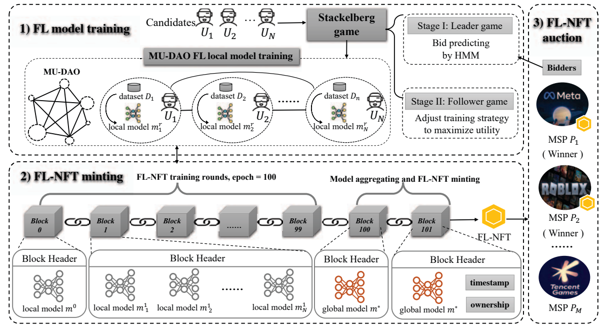

Fig. 1. The proposed system model based on blockchain. 1) FL model training process by Stackelberg game. 2) FL-NFT minting process based on blockchain 3) MSPs bid for FL-NFT by auction mechanism.

III. System Model

In the Metaverse service, an incredible amount of digital content created by MUs, i.e., UGC. In order to protect the ownership of creators, UGC can be minted to NFT via blockchain for collecting, trading, and accessing.

A. FL-NFT auction model based on blockchain

We consider an FL-NFT auction model based on blockchain with N Metaverse users (MUs) denoted by $\mathcal{U} = \{U_1, U_2, \ldots, U_N\}$ and M Metaverse service providers (MSPs) denoted by $\mathcal{P} = \{P_1, P_2, \ldots, P_M\}$. For any MU U_i with dataset $\mathcal{D}_i = \{(x_1, y_1), (x_2, y_2), \ldots, (x_d, y_d)\}$, the loss function $L(\cdot)$ [18] can quantify the difference between the predictive value $f(m_i, x_l)$ and labeled value y_l. For MU-DAO, the target of FL tasks is to minimize the loss function $L(\cdot)$ as

$$\mathcal{T}(m_i^t) = arg \min_{m_i^{t-1}} \left\{ \frac{1}{d} \sum_{l=1}^{d} L\left(f\left(m_i^{t-1}, x_l\right), y_l\right) \right\}, \quad (1)$$

m_i^t is the parameters of the local model trained by U_i in the t-th iteration , d is the size of local dataset.

The proposed system model based on blockchain consists of three phases: FL model training, FL-NFT minting, and FL-NFT auction, as shown in Fig. 1.

1) FL model training: MUs are organized in a decentralized autonomous organization (i.e., MU-DAO) to participate in the

FL model training collaboratively after MUs decide on their training strategies by the Stackelberg game. MU-DAO initializes the FL model parameters according to the chosen machine learning model, broadcasts them to MUs which begins local model training. The MU-DAO aggregates local models of MUs by smart contract. The local models are updated based on the mini-batch stochastic gradient descent algorithm [19].

2) FL-NFT minting: The smart contract serves as the minter, which is responsible for collecting the model parameters m^*, the minting timestamp τ_{m^*}, and the public key of MU-DAO, etc. Then, the minter packages this information to a file named fl-nft.js, which is recorded in the blockchain to ensure that FL-NFT is genuinely decentralized. The ownership of FL-NFT belongs to the whole MU-DAO and allows FL-NFTs to be sold by the consensus within MU-DAO.

3) FL-NFT auction: MSPs offer bids to the blockchain-based auction platform, where the winner determination is implemented in the auction smart contract to realize automatic auction execution. Due to heterogeneity between MUs in computing, storage, communication resources, and data quality, there are free-rider and unfairness issues. Therefore, it is necessary to trade off the cost and benefit to encourage more MUs to participate in MU-DAO fairly.

B. FL Cost-benefit Framework of the Metaverse Users

In this paper, we mainly consider computation and privacy cost. The cost function of U_i to perform FL training task can be expressed as

$$C_i = C_i^c k_i + C_i^p \epsilon_i, \forall k_i \in \mathbb{Z}^+, \forall \epsilon_i \in \mathbb{R}^+, \tag{2}$$

where C_i^c and C_i^p denote the unit cost factors of computation resource consumption and privacy disclosure, respectively. k_i and ϵ_i are the iterations of local model and the differential privacy budget [20], respectively.

- *Computation cost factor C_i^c:* We denote the CPU performance of MUs for model training by f_i (i.e., CPU clock frequency). Moreover, the average memory occupation ratio and memory occupation ratio are denoted by ξ_i and θ_i, respectively. Then, the memory occupation for local model training is $\xi_i\theta_i$. Based on the secondary energy consumption model of CPU [21], the unit computation cost of model iteration can be defined as

$$C_i^c = \alpha \zeta z_i s_i f_i^2 + (1-\alpha)\,\xi_i\theta_i, \tag{3}$$

  where α is the computation cost adjustment factor, ζ is the effective capacitance [22], z_i is the CPU cycle when handling one batch of data, and s_i is the batch size for each iteration of the local model.
- *Privacy cost factor C_i^p:* In order to minimize the risk of privacy disclosure when sharing the local model in MU-DAO, the privacy cost of intermediate parameters is considered. Inspired by [23], we adopt gradient-norm to measure the privacy preference. Thus, the per unit cost of privacy disclosure C_i^p can be defined as

$$C_i^p = \beta \ln\left(1 + \left\| \bigtriangledown \widetilde{g}\left(m_i^t, b_i\right) \right\|\right), \tag{4}$$

  where β is the privacy cost adjustment factor, the smaller the privacy budget ϵ_i is, the greater the noise disturbance and the lower the model quality could be.

In FL-NFT minting process, MUs adjust training strategies, including local iterations and privacy budget, to maximize their benefits. Unlike the traditional FL incentive mechanism, considering the immersive experience in Metaverse, both the model quality and freshness need to be considered. Therefore, we combine model quality $Q_j^{m^*}$ and freshness $F_j^{m^*}$ to measure the satisfaction of MSP P_j for the FL-NFT m^* as

$$\varphi_j^{m^*} = \left(Q_j^{m^*}\right)^{e_j^Q} + \left(F_j^{m^*}\right)^{e_j^F} = \left(Q_j^{m^*}\right)^{\lambda} + F_j^{m^*}, \tag{5}$$

$$s.t.\ \lambda = \frac{e_j^Q}{e_j^F} > 0, 0 < e_j^Q \leq 1, 0 < e_j^F \leq 1, e_j^Q + e_j^F = 1, \tag{6}$$

where e_j^Q and e_j^F are attention coefficient [1] of model quality $Q_j^{m^*}$ and freshness $F_j^{m^*}$ determined by P_j, respectively.

The rationale behind $Q_j^{m^*}$ and $F_j^{m^*}$ is the contribution of MUs in FL model training, higher contribution of MUs leads to higher satisfaction for MSPs. Let θ_i^Q and θ_i^F be the satisfaction contribution in model quality and freshness for U_i, respectively. We have $Q_j^{m^*} = \sum_{i=1}^N \theta_i^Q$ and $F_j^{m^*} = \sum_{i=1}^N \theta_i^F$. We define satisfaction contributions for U_i as follows:

- *The model quality contribution θ_i^Q:* For U_i, the model quality contribution is determined by its local models quality and raw data quantity (i.e., the local data size used for training). However, there may be a large amount of redundant data in the training data, so the contribution evaluated by the total training data size is one-sided. It is more practical to incorporate data quality based on cross-entropy [24] as $H_i = -\sum_{i=l}^d y_l log f(x_l)$, where $f(x_l)$ is the predict value by function $f(\cdot)$ and y_l is the labeled value. Therefore, θ_i^Q can be denoted as

$$\theta_i^Q = \frac{\mu_0 |\mathcal{D}_i|}{\mu_1 - \frac{1}{R}\sum_{i=1}^R y_i log f\left(x_i\right)}, \tag{7}$$

  where, $u_0 > 0$ and $u_1 > 0$ are the model utility parameters, which are set according to the loss function, neural network structure and data distribution [25]. In this paper, u_0 represents the number of model hidden layers, u_1 represents the number of model output layers, R represents the total round of U_i participates in FL.
- *The model freshness contribution θ_i^F:* Metaverse services allow users to immerse themselves via life-like real-time interaction. The fresher FL-NFT leads to more accurate prediction, resulting in better immersive experiences. Inspired by existing work [26], the metric of age of information (AoI) can be used to denote the duration of MUs participating in FL-NFT minting. For U_i, the

[1] $e_j^Q = 1$ and $e_j^F = 1$ denote that only model quality or freshness is considered by P_j; $e_j^Q + e_j^F = 1$ denotes that both model quality and freshness are taken into account by P_j.

duration T_i mainly includes the time of training T_i^m, uploading T_i^l and consensus T_i^c, denoted as

$$T_i = T_i^m + T_i^l + T_i^c, \tag{8}$$

where $T_i^m = log(1/H_i)\frac{\mathcal{D}_i}{f_i}$, the smaller the value H_i is, the higher accuracy of the local model could be. Furthermore, the communication resource ϖ_i (i.e., bandwidth) used by U_i, defined as $T_i^l = \frac{d_i}{\varpi_i log_2(1+\vartheta_i)}$, where ϑ_i denotes the Signal-to-Interference-plus-Noise Ratio (SINR) for the communication channel. T_i^c mainly depends on different consensus algorithm. A small value of T_i indicates fisher local model, so the model freshness contribution θ_i^F can be defined as equation (9), which is upper bounded by $\mathcal{O}(log(1/T_i))^9$.

$$\theta_i^F = log(1/T_i), \tag{9}$$

Under rational auction market, U_i can get benefit ratio from the bids of FL-NFT, which is determined by their model quality contribution ratio $\tau_i^Q = \frac{\theta_i^Q}{\sum_{i=1}^N \theta_i^Q}$ and freshness contribution ratio $\tau_i^F = \frac{\theta_i^F}{\sum_{i=1}^N \theta_i^F}$. Therefore, the benefit of U_i from bid of P_j can be formulated as

$$\delta_{ij} = q_j \left(Q_j^{m^*}\right)^{\lambda} \tau_i^Q + f_j F_j^{m^*} \tau_i^F, \tag{10}$$

where q_j and f_j are MSP P_j's unit satisfaction bidding strategies for $Q_i^{m^*}$ and $F_i^{m^*}$, respectively.

IV. Strategy Optimization Based on Stackelberg Game

In this section, we construct an imperfect information Stackelberg game (IISG) [27] to trade off the cost and benefit by optimizing the action strategies of MUs and MSPs.

A. Stackelberg Game Formulation

In IISG, we assume that MSPs and MUs are all rational individuals, in which MUs can make the decision in distributed manner within MU-DAO. We model the auction interactions among MSPs and MUs as a multi-leader multi-follower IISG, in which the MSPs are leaders and MUs are followers.

1) Training strategy optimization of MU in Stage II

In Stage II of IISG, each rational MU U_i can adjust training strategies (i.e., local iterations and privacy budget) according to the bids offered by the MSPs within a given game decision period T. Let $\boldsymbol{K}_i \triangleq (k_{i1}, k_{i2}, \ldots, k_{iM})$ and $\boldsymbol{E}_i \triangleq (\epsilon_{i1}, \epsilon_{i2}, \ldots, \epsilon_{iM})$ be the local iterations and privacy budget of U_i to the FL-NFTs demanded by MSPs $\mathcal{P}$. The optimization problem for MU U_i within given game decision period T can be formulated as

Problem 1

$$\max \Phi_i\left(\boldsymbol{K}_i, \boldsymbol{E}_i\right) = \sum_{j=1}^{M} \delta_{ij}\Lambda_{ij} - C_i, \tag{11}$$

$$\begin{aligned} s.t.\ & C1: C_i \leq \sum_{j=1}^{M} \delta_{ij}\Lambda_{ij}, \forall j, \\ & C2: \frac{k_{ij}}{\zeta z_i s_i f_i^2} + \frac{z_i s_i}{b_i} \leq T, \end{aligned} \tag{12}$$

where $\Lambda_{ij} = h(k_{ij}) + h(\epsilon_{ij})$ indicates the benefit of MUs enjoying the Metaverse service, $h(x)$ is the σ-fair function adopted in [28] defined as $h(x) = \frac{1}{1-\sigma}x^{1-\sigma}$ [2], δ_{ij} is the benefit of MU U_i from the bid of MSP P_j, b_i is the bandwidth used for consensus communication with U_i. $C1$ ensures that MU's total cost cannot exceed the budget constraint of MSPs, indicating that the budget balance of the auction market. $C2$ expresses that the MU's decision time cannot exceed the game decision period T.

2) Bidding Strategy of MSPs in Stage I

In Stage I of IISG, each rational MSP P_j determines bidding strategies (i.e., bids of model quality and freshness) according to the satisfaction to the FL-NFT, which are related with the training strategies of MUs. Let $\boldsymbol{Q}_j \triangleq \{q_{1j}, q_{2j}, \ldots, q_{Nj}\}$ and $\boldsymbol{F}_j \triangleq \{f_{1j}, f_{2j}, \ldots, f_{Nj}\}$ denote bids of model quality and freshness offered by MSP P_j accroding to the contribution ratio of MUs $\mathcal{U}$, respectively. Then, the optimizaiton problem for MSP P_j can be formulated as

Problem 2

$$\max \Psi_j\left(\boldsymbol{Q}_j, \boldsymbol{F}_j\right) = \sum_{i=1}^{N} \left(q_{ij}w_{ij}^q + f_{ij}w_{ij}^f - \delta_{ij}\right), \tag{13}$$

$$\begin{aligned} s.t.\ & C1: \sum_{i=1}^{N} (q_{ij} + f_{ij}) \leq B_j, \forall j, \\ & C2: t_j \leq T, \forall j, \end{aligned} \tag{14}$$

where w_{ij}^q and w_{ij}^f are the winning probability for q_{ij} and f_{ij}, respectively, t_j is the bidding decision time of MSP P_j. $C1$ ensures that the total bids are no more than the budget constraint for MSP P_j. $C2$ expresses that the decision time is limited. The winning probability for MSP is relevant to the proportion of the total bid in general, which can be denoted as $w_{ij}^q = \frac{q_{ij}}{\left(q_{ij}+\sum_{ij',j'\neq j}^{m} q_{ij'}\right)}$ and $w_{ij}^f = \frac{f_{ij}}{\left(f_{ij}+\sum_{ij',j'\neq j}^{m} f_{ij'}\right)}$ [3].

B. Solving Stackelberg Equilibrium of IISG

In this section, we solve the Stackelberg equilibria of IISG by the backward induction methods, where the existence of the equilibrium is investigated by the negative definite of the Hessian matrix, and the first-order partial derivative of utility derives the unique subgame equilibrium [29].

Theorem 1. *The existence and uniqueness of the subgame equilibrium for MUs in* ***Problem 1*** *can be guaranteed, i.e., every MU has an optimal and unique training strategy $(\boldsymbol{K}_i^*, \boldsymbol{E}_i^*)$ for the number of local iterations and privacy budget.*

[2] $h(x)$ is non-decreasing and concave, i.e., $\frac{\partial h(x)}{\partial x} \geq 0$ and $\frac{\partial^2 h(x)}{\partial x^2} < 0$, which indicates decreasing marginal utility for MU to the Metaverse service.

[3] The parameters $q_{ij'}$ and $f_{ij'}$ are the predicted bids of other competitors excepting P_j for model quality and freshness, respectively.

Proof. In order to guaranty the existence, we observe the Hessian matrix of $\Phi_i(\boldsymbol{K}_i, \boldsymbol{E}_i)$ with respect to $\boldsymbol{K}_i$ is

$$H(\Phi_i) = \begin{bmatrix} \frac{\partial^2 \Phi_i}{\partial \boldsymbol{K}_i^2} & \frac{\partial^2 \Phi_i}{\partial \boldsymbol{K}_i \partial \boldsymbol{E}_i} \\ \frac{\partial^2 \Phi_i}{\partial \boldsymbol{E}_i \partial \boldsymbol{K}_i} & \frac{\partial^2 \Phi_i}{\partial \boldsymbol{E}_i^2} \end{bmatrix} = diag(H_{ij}^K, H_{ij}^E), \tag{15}$$

and

$$\begin{aligned} H_{ij}^K &= \left[\tfrac{\partial^2 \Phi_i(\boldsymbol{K}_i, \boldsymbol{E}_i)}{\partial k_{ij} \partial k_{ij'}}\right]_{j,j' \in \{1,2,\ldots,M\}} \\ &= -diag(h_{i1}^k, h_{i2}^k, \ldots h_{ij}^k) < 0, \end{aligned} \tag{16}$$

where $h_{ij}^k = \delta_{ij} k_{ij}^{-\sigma-1}$. It is clearly that H_{ij}^K is negative definite. Then, we derive the second derivative of $\Phi_i(\boldsymbol{K}_i, \boldsymbol{E}_i)$ with respect to $\boldsymbol{E}_i$ as follows

$$\begin{aligned} H_{ij}^E &= \left[\tfrac{\partial^2 \Phi_i(\boldsymbol{K}_i, \boldsymbol{E}_i)}{\partial \epsilon_{ij} \partial \epsilon_{ij'}}\right]_{j,j' \in \{1,2,\ldots,M\}} \\ &= -diag(h_{i1}^\epsilon, h_{i2}^\epsilon, \ldots h_{ij}^\epsilon) < 0, \end{aligned} \tag{17}$$

where $h_{ij}^\epsilon = \delta_{ij} \epsilon_{ij}^{-\sigma-1}$. We can easily derive that H_{ij}^E is negative definite, and thus $H(\Phi_i)$ is negative definite and $\Phi_i(\boldsymbol{K}_i, \boldsymbol{E}_i)$ is concave. Therefore, it can be proved that the existence of equilibrium solution $(\boldsymbol{K}_i^*, \boldsymbol{E}_i^*)$ in **Problem 1**.

We further take the first-order partial derivative of Φ_i to obtain the equilibrium solution as follows

$$(\boldsymbol{K}_i^*, \boldsymbol{E}_i^*) = [(\sqrt[-\sigma]{C_i^c/\delta_{ij}},\ \sqrt[-\sigma]{C_i^p/\delta_{ij}})]. \tag{18}$$

Since the numbers of local iterations of MUs are within the positive integer space $\mathbb{Z}^+$. MUs can tune the real number of local iterations conducted by Stackelberg game through the following equation

$$\boldsymbol{K}_i^{r*} = \lceil \boldsymbol{K}_i^* \rceil, \tag{19}$$

where $\lceil x \rceil$ is the integer function, denote that $\lceil x \rceil = min\{\varsigma \in \mathbb{Z}, \varsigma \le n\}$. So far, we have solved the Stackelberg equilibrium in **Problem 1**. By analyzing any utility Ψ_i for MSP P_j given in (13) and condition given in (14), we can further investigate the properties of $\Psi_i(\cdot)$ as follows.

Theorem 2. *The existence and uniqueness of the subgame equilibrium for MSPs in **Problem 2** can be guaranteed, i.e., each MSP has an optimal and unique bidding strategy $(\boldsymbol{Q}_j^*, \boldsymbol{F}_j^*)$ for the bids of model quality and freshness.*

Proof. We present the Hassian matrix of $\Psi_j(\boldsymbol{Q}_j, \boldsymbol{F}_j)$ with respect to bidding strategies $\boldsymbol{Q}_j$ as follows

$$H(\Psi_j) = \begin{bmatrix} \frac{\partial^2 \Psi_j}{\partial \boldsymbol{Q}_j^2} & \frac{\partial^2 \Psi_j}{\partial \boldsymbol{Q}_j \partial \boldsymbol{F}_j} \\ \frac{\partial^2 \Psi_j}{\partial \boldsymbol{F}_j \partial \boldsymbol{Q}_j} & \frac{\partial^2 \Psi_j}{\partial \boldsymbol{F}_j^2} \end{bmatrix} = diag(H_{ij}^Q, H_{ij}^F), \tag{20}$$

and

$$\begin{aligned} H_{ij}^Q &= \left[\tfrac{\partial^2 \Psi_j(\boldsymbol{Q}_j, \boldsymbol{F}_j)}{\partial q_{ij} \partial q_{i'j}}\right]_{i,i' \in \{1,2,\ldots,N\}} \\ &= -diag(h_{i1}^q, h_{i2}^q, \ldots h_{ij}^q) < 0, \end{aligned} \tag{21}$$

where

$$h_{ij}^q = \frac{w_{ij}^q}{q_{ij}} + \frac{(\sum_{i',i'\ne i}^n q_{i'j}) + \sum_{i',i'\ne i}^n q_{i'j}}{(q_{ij} + \sum_{i',i'\ne i}^n q_{i'j})^3}. \tag{22}$$

It is clear that H_{ij}^Q is negative definite. Then, we derive the second derivative of $\Psi_j(\boldsymbol{Q}_j, \boldsymbol{F}_j)$ with respect to $\boldsymbol{F}_j$ as

$$\begin{aligned} H_{ij}^F &= \left[\tfrac{\partial^2 \Psi_j(\boldsymbol{Q}_j, \boldsymbol{F}_j)}{\partial f_{ij} \partial f_{i'j}}\right]_{i,i' \in \{1,2,\ldots,N\}} \\ &= -diag(h_{i1}^f, h_{i2}^f, \ldots h_{ij}^f) < 0, \end{aligned} \tag{23}$$

where

$$h_{ij}^f = \frac{w_{ij}^f}{f_{ij}} + \frac{(\sum_{i',i'\ne i}^n f_{i'j}) + \sum_{i',i'\ne i}^n f_{i'j}}{(f_{ij} + \sum_{i',i'\ne i}^n f_{i'j})^3}. \tag{24}$$

We can easily derive that H_{ij}^F is negative definite, and thus $H(\Psi_j)$ is negative definite and $\Psi_j(\boldsymbol{Q}_j, \boldsymbol{F}_j)$ is concave. Therefore, it can be proved that **Problem 2** has a unique optimal solution $(\boldsymbol{Q}_j^*, \boldsymbol{F}_j^*)$. By taking the first-order partial derivative of $\Psi_j(\boldsymbol{Q}_j, \boldsymbol{F}_j)$, we obtain the equilibrium solution as follows

$$(\boldsymbol{Q}_j^*, \boldsymbol{F}_j^*) = [(\sqrt{\frac{\Delta_q^2 + \Delta_q}{\left(Q_j^{m^*}\right)^\lambda + 1}} - \Delta_q,\ \sqrt{\frac{\Delta_f^2 + \Delta_f}{F_j^{m^*} + 1}} - \Delta_f)], \tag{25}$$

where

$$\begin{cases} \Delta_q = \sum_{i',i'\ne i}^n q_{i'j} \\ \Delta_f = \sum_{i',i'\ne i}^n f_{i'j} \end{cases}. \tag{26}$$

Therefore, the Stackelberg equilibrium can be achieved through **Theorem 1** and **2**. Both MUs and MSPs can derive their optimal training strategies $(\boldsymbol{K}_j^*, \boldsymbol{E}_j^*)$and bidding strategies $(\boldsymbol{Q}_j^*, \boldsymbol{F}_j^*)$, respectively. None of them tends to adjust their strategies to gain higher utilities.

Theorem 3. *The proposed incentive mechanism achieves individual rationality (IR).*

Proof. For each MU $U_i \in \mathcal{U}$, by observing the utility function in Eq.(11) and the constraint $C1$ in Eq.(12) we have $\Phi_i = \sum_{j=1}^M \delta_{ij} \left(h\left(k_{ij}\right) + h\left(\epsilon_{ij}\right)\right) - C_i \ge 0$. Thus, for each MU $U_i \in \mathcal{U}$, the utility $\Phi_i \ge 0$.

For each MSP $P_j \in \mathcal{P}$, it will win the auction only when $w_{ij}^q = w_{ij}^f = 1$. According to McAfee's double auction, the bids of winners satisfy $q_{ij} + f_{ij} \ge \delta_{ij}$. By combining the constraint $C1$ in Eq.(14) we have

$$\Psi_j = \sum_{i=1}^N \left(q_{ij} + f_{ij} - \delta_{ij}\right) \ge 0. \tag{27}$$

Thus, for each MSP $P_j \in \mathcal{P}$, the utility $\Psi_j \ge 0$. So, the proposed incentive mechanism achieves incentive rationality.

Theorem 4. *The proposed incentive mechanism achieves incentive compatibility (IC).*

Proof. In the phase of FL-NFT minting, the MUs optimal their training strategies $(\boldsymbol{K}_i, \boldsymbol{E}_i)$ and MSPs optimal their bidding strategies $(\boldsymbol{Q}_j, \boldsymbol{F}_j)$ based on IISG. The sell-bids and buy-bids offered by the MU-DAOs and MSPs are based on their true evaluation of FL-NFT value because of the payment scheme based on the second price auction. In our scheme, for each MSP P_j, it satisfies $E(\Psi_j(\boldsymbol{Q}_j^*, \boldsymbol{F}_j^*)) \ge E(\Psi_j(\boldsymbol{Q}_j, \boldsymbol{F}_j))$, and for each MU U_i it satisfies $E(\Phi_i\left(\boldsymbol{K}_i^*, \boldsymbol{E}_i^*\right)) \ge E(\Phi_i\left(\boldsymbol{K}_i, \boldsymbol{E}_i\right))$. Given a clearing price of FL-NFT, each buyer $P_j \in \mathcal{P}$ and seller $U_i \in \mathcal{U}$ cannot improve their utilities by submitting untruthful bids. Therefore, the proposed mechanism achieves incentive compatibility.

V. SIMULATION AND EVALUATION

We conduct experimental simulations to evaluate the convergence performance of FL-NFT and verify the effectiveness of our proposed scheme IISG.

A. Simulation Settings

We simulate an MU-DAO by recruiting 10 MUs to participate in FL-NFT training and minting. The simulation environment is a server with an Apple M1 chip of 8-core CPU and 8GB RAM, and land in macOS Big Sur v11.5.2 operating system with Python v3.6.10 and PyTorch v0.4.1. Under the simulation scenario, the MNIST [30] and CIFAR10 [31] datasets are divided equally into 10 MUs. The neural networks select multi-layer perceptron (MLP) [32] and convolutional neural networks (CNN) [33] for model training, which can be aggregated by FedAvg [25] to update the model parameters.

Each MU executes the mini-batch stochastic gradient descent algorithm [19] to optimize the local model and complete the cooperative training within MU-DAO. We adjust hyper-parameters for all datasets and models to the best result among 5 runs. All experiments are conducted through a lightweight FL open source framework[4] as the benchmark, which sets the clients to participate in FL randomly. We adjust the super parameter settings of all methods for comparison and reported the best results of each method in 3 repeated runs. The specific experimental parameter settings are shown in Table I.

TABLE I
EXPERIMENTAL PARAMETER SETTINGS

Parameters	**Value**
Number of MUs	$N = 10$
Number of MSPs	$M = 5$
SGD momentum	$\mathcal{M}_s = 0.5$
Total budget of MSPs	$B_j = 1000$
Model utility parameters	$\mu_1 = 10, \mu_2 = 2$
Model training parameters	$lr = 0.01, bs = 64, k_i^0 = 5$
CPU clock frequency of MUs	$f_i \in [3, 5]$GHz
Privacy budget of MUs	$\epsilon_i \in [1, 5]$
Game decision period	$T = 10s$
Regulatory factor	$\alpha = 0.3, \beta = 0.5, \xi_i = 0.5, \theta_i = 8$

B. Results and Analysis

We first compare the quality of the learning model which was minted to NFT in our IISG with other three schemes, including *random-FL, loss-based and gradient-norm* [34] as shown in Fig. 2. In IISG, MUs can adjust the training strategies to organize MU-DAO voluntarily for FL model training based on the IISG. Random-FL is the selected benchmark scheme. *Loss-based* and *gradient-norm* are other two state-of-the-art training strategies [34], which adjust FL participants according to training-loss and gradient-norm, respectively.

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In Fig. 2(a), the accuracy of FL model improves from 95.69% to 98.39% after 100 epochs. In Fig. 2(b), the test accuracy improves 11.49%. In Fig. 2(c), four schemes outperform than MLP model in terms of both accuracy and convergence speed. All schemes get better test accuracy than MLP model, but the test accuracy of FL-NFT only improve 0.91%. In the Fig. 2(d), we can see that when the epoch is 100, the accuracy of *IISG* is 67.19%, which is 16.96%, 9.48% and 12.09% higher than those of *random-FL loss-based*, and *gradient-norm*, respectively. This is because the local iterations and privacy budget can be adjusted according to the costs and benefits of MUs in *IISG*, leading to more rewards from MSPs.

The reason behind it is that the training strategies, including local iterations and privacy budget, can be dynamically adjusted according to the costs and utility of MUs in our scheme. As a result, the MUs are encouraged to allocate resources reasonably to provide more high-quality models. Some fluctuations are normal for the different models and datasets for model training. As expected, lower test accuracy is achieved in the CIFAR-10 dataset for both models and under different datasets. It can be seen that the test accuracy of random-FL is the lowest, as MUs randomly adjust training strategies regardless of different cost and utility situations.

VI. CONCLUSION

In this paper, we have proposed an effective ownership tokenization scheme and an incentive mechanism for learning-based UGC in the blockchain-driven Metaverse. Specifically, we have established a decentralized MU-DAO to mint FL-NFT. The imperfect information Stackelberg game (IISG) has been adopted to model the auction interactions among MUs and MSPs under the FL cost-benefit framework to maximize their utility. The backward induction has been adopted to solve the equilibrium solution. Numerical results by the simulations have shown that the quality of learning model minted to NFT can be increased compared with the existing schemes.

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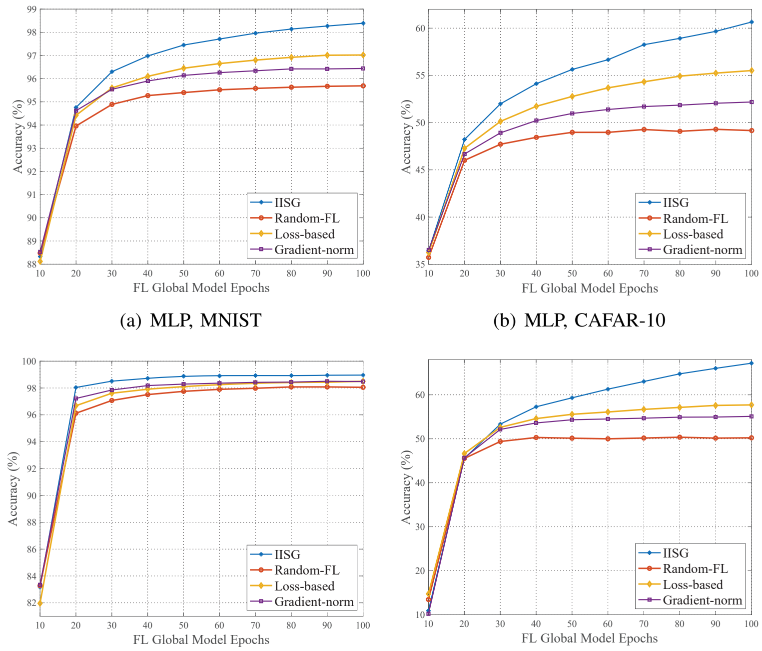

(a) MLP, MNIST (b) MLP, CAFAR-10

(c) CNN, MNIST (d) CNN, CAFAR-10

Fig. 2. Test accuracy against FL global model epochs for training different models and datasets with four schemes.

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