A Privacy-preserving Auction Mechanism for Learning Model as an NFT in Blockchain-Driven Metaverse

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The Metaverse, envisioned as the next-generation Internet, will be constructed via twining a practical world in a virtual form, wherein Meterverse service providers (MSPs) are required to collect massive data from Meterverse users (MUs). In this regard, a critical demand exists for MSPs to motivate MUs to contribute computing resources and data while preserving user privacy. Federated learning (FL), as a privacy-preserving collaborative machine learning paradigm, can support distributed intensive computation in Metaverse. In this work, we first investigate minting the machine learning models into NFT with FL assistance (referred to as FL-NFT), such that MUs as stakeholders can control the ownership and share the economic value of user-generated content (UGC). Specifically, MUs are encouraged to establish a decentralized autonomous organization (i.e., MU-DAO) to aggregate local models and mint FL-NFT. MUs and MSPs optimize the strategies by formulating an imperfect information Stackelberg game (IISG) to trade off the cost and benefit. We apply the backward induction to derive the equilibrium solution. Then, we construct a privacy-preserving multi-winner sealed-bid auction mechanism (PMS-AM), in which the Hidden Markov Model (HMM) assists MSPs in choosing rational bidding strategies according to historical bids, and the double auction mechanism determines the winners and price of FL-NFT. Finally, the numerical results based on theoretical analysis and simulations demonstrate that the proposed PMS-AM can increase the quality of FL-NFT and achieve the economic properties of incentive mechanisms such as individual rationality and incentive compatibility.

CCS Concepts: • **Theory of computation → Algorithmic game theory and mechanism design**; *Market equilibria.*

Additional Key Words and Phrases: Metaverse, blockchain, federated learning, NFT, auction mechanism, Stackelberg game, HMM

1 INTRODUCTION

The rapid development of emerging communication and multimedia technologies, such as beyond 5G/6G, augmented reality (AR), virtual reality (VR), mixed reality (MR) and the tactile internet (TI) make it possible for users to immerse in various Metaverse services physically [26], including entertainment [21], visual campus [8],

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healthcare [57], e-commerce [17], smart city [24], and digital twin (DT) [50], etc. In 1992, the word "Metaverse" first appeared in the science fiction *Snow Crash* of Neal Stephenson [19]. In 2021, Facebook was even rebranded as "Meta", which brought the Metaverse back to cutting-edge discussions. Many lite Metaverse games, such as Roblox and Fortnite, have been pursued by extensive users. Some technology giants have been involved in Metaverse services, including Microsoft, Apple, Google, Tencent, Baidu, etc. Microsoft partner has proposed a new MR solution called HoloLens [15] for training, learning, and work. Google is also introducing immersive views and the geospatial API for Google Maps that could support the AR experience. Although increasing Metaverse services are emerging, it is still far from the ultimate Metaverse with the feature of immersion, embodiment, universality, and interoperability [53]. In the upcoming Web 3.0, Metaverse can provide a decentralized immersive virtual world, where Metaverse users (MUs) as stakeholders will be able to build the autonomous ecosystem and share the economic value.

In Metaverse services, the MUs can play as avatars immersing in the 3-dimensional (3D) virtual world by accessing the seamless Metaverse service developed by various Metaverse service providers (MSPs). In order to support real-time and immersive experiences for MUs, intensive rendering computation and low-latency communication are required. For example, there are many MUs with viewpoint changing dynamically, in which the tiled video [7] needs to be rendered in real-time. Assisted by edge computing, the rendering tasks can be offloaded to VR devices at edge networks to reduce the communication delay significantly, especially for some delay-sensitive tasks (e.g., VR viewpoint prediction). Moreover, the forecast pixels that are watched can be transmitted ahead of time, so the tiling of VR video saves bandwidth and reduces transmission delay significantly [53]. However, there is still resource overhead and risk of privacy disclosure, thereby an incentive mechanism needs to be designed to subsidize the participating cost of MUs.

1.1 Research Motivation

The ecosystem established by MUs has recently become a promising topic for driving innovations toward Metaverse applications. Blockchain-driven Metaverse has recently attracted extensive attention due to its decentralized characteristics, where autonomous ecosystems based on blockchain bring feasible infrastructure to enable the decentralized Metaverse. The ubiquitous Metaverse services require a decentralized autonomous ecosystem to address the critical issue of monopolists and dictators in the Metaverse. MUs, as essential stakeholders, need to get benefit from this ecosystem, in which they can create a large number of user-generated content (UGC) (e.g., avatar models).

Federated learning (FL) [22] as a privacy-preserving collaborative machine learning paradigm [43] can be used to organize MUs to facilitate the creation of UGC in the form of FL global models (i.e., FL-NFTs), which can support intensive computation by collective efforts. In fact, the decentralized federated learning marketplace is a huge industry with good business prospects. There is an assured demand for companies to buy and sell valuable learning models through a service interface, including finance, healthcare, map navigation, etc. There are some real-world data marketplaces, like Dawex[1], Lotame[2], and Oracle BlueKai[3]. For example, Dawex builds a trusted AI marketplace to support AI model providers, data providers and AI model users conducting AI-data transactions. In this regard, federated learning as a distributed machine learning paradigm can transform data without getting access to the raw data.

In edge-enabled Metaverse, obtaining a high-quality FL model requires all participant MUs to exert enough effort, such as CPU, storage, and bandwidth resources. Although the models can be trained when the computation resources are idle, achieving effective and fair FL in the Metaverse is still practically impossible without reasonable

[1] https://www.dawex.com/en/news/making-ai-promise-reality-with-ai-marketplaces/
[2] https://www.lotame.com/
[3] https://www.oracle.com/cx/marketing/data-management-platform/

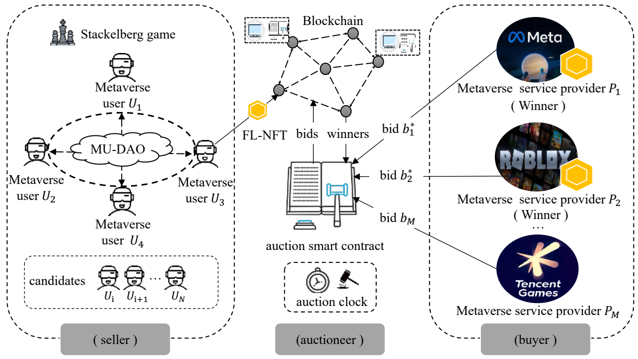


Fig. 1. Metaverse service providers bid for FL-NFT by auction smart contract from MU-DAO.

incentive mechanisms. A few incentive mechanisms for FL have been proposed, but they are not directly applicable in the Metaverse scenario. In this paper, we are particularly interested in studying an incentive mechanism to encourage MUs to participate in a decentralized autonomous organization (i.e., MU-DAO) to mint FL-NFT cooperatively. There are still some critical challenges to be dealt with, as described below.

C1. How to trade off the cost and benefit of MUs in the process of FL-NFT minting based on blockchain?

C2. How to determine a reasonable price of FL-NFT to realize individual rationality and market equilibria?

1.2 Our Contributions

To mitigate the above critical challenges, we introduce a privacy-preserving multi-winner sealed-bid auction mechanism (PMS-AM) to assist MSPs in bidding for the FL-NFT, as shown in Fig. 1. Specifically, MUs are encouraged to establish a decentralized autonomous organization MU-DAO to train FL local models and aggregate global models, which can be minted into Non-Fungible Tokens (i.e., FL-NFT). A blockchain-based auction smart contract as the auctioneer determines multiple winners according to bids of MSPs, where the higher the bid and the priority with accessing FL-NFT can be released until the auction clock expires. We extend the double auction mechanism for FL-NFT based on our previous work [41]. The main contributions of this paper are summarized as follows:

- We investigate minting the federated learning models into NFT (i.e., FL-NFT), encouraging MUs as stakeholders to participate in FL model minting and share the economic value. In order to mitigate the issue of monopolists and dictators in Metaverse, participating MUs establish a decentralized autonomous organization MU-DAO to train the FL global model collaboratively and mint it to an FL-NFT.
- Considering the instability of the auction market, we formulate the imperfect information Stackelberg game (IISG) to optimize the training strategies of MUs and the bidding strategies of MSPs, which realizes utility maximization and individual rationality. We adopt the backward induction to derive the equilibrium solution and prove the existence and uniqueness of the Stackelberg equilibrium.
- In order to price FL-NFT reasonably, a privacy-preserving multi-winner sealed-bid auction mechanism (PMS-AM) is proposed, where the auction smart contract acts as auctioneer to manage and control the trading of the FL-NFT in a distributed manner. The Hidden Markov Model (HMM) is utilized to assist MSPs in choosing rational bidding strategies. We conduct some simulations to validate the effectiveness of PMS-AM.

The remainder of this paper is organized as follows. In Section 2, we review related works and drawbacks. Section 3 presents the FL-NFT auction model and FL cost-benefit framework. Section 4 gives the strategies optimization of MUs and MSPs based on the IISG. In Section 5, the auction process of FL-NFT by PMS-AM is proposed. We conduct simulations and present the numerical results in Section 6. Finally, we conclude the paper in Section 7.

2 RELATED WORK

In this section, we briefly review the related research about auction and incentive mechanisms that can be used in Metaverse. We then discuss the role of blockchain and federated learning in Metaverse.

2.1 Auction and Incentive Mechanism in Metaverse

In Metaverse service, UGC refers to a form of different digital content generated by MUs' contribution, which contains personal privacy data and potential economic value. For blockchain-driven Metaverse, there are surging need for UGC to share its economic value among all stakeholders. Some researchers have focused on incentive and auction mechanisms for generating UGC. Xu et al. [54] 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 services. Jiang et al. [18] adopted the Coded Distributed Computing (CDC) scheme to support rendering computation in Metaverse services, where a hierarchical structure composed of a coalition game and Stackelberg game was designed to choose reliable workers to participate in the rendering tasks. Sun et al. [46] investigated dynamic digital twin (DT) and formulated a two-stage Stackelberg game to incentive users to participate in aerial-assisted Internet of Vehicles (IoV). Lin et al. [30] proposed an incentive-based congestion control scheme for Digital Twin Edge Networks (DTENs), in which the Lyapunov optimization theory [3] was adopted to decompose the long-term control decision into a series of online associate decisions.

Without a reasonable incentive mechanism, MUs are unwilling to contribute computation and data resources to participate in Metaverse service computing under the risk of privacy disclosure. Many existing incentive mechanisms of Metaverse focus on the resource allocation rules, while they lose sight of the economic value contained in UGC and the nature of public goods [44]. The auction mechanism is designed to stimulate buyers to bid their actual valuations for UGC ownership, but the potential risks of decision privacy lead to an unfair auction market. Wang et al. [48] proposed a privacy-preserving and truthful double auction mechanism PS-TAHES based on additive homomorphic encryption [38] to prevent personal privacy information leakage in the auction. However, research on incentive mechanisms in Metaverse is still in its infancy and they rarely regard privacy concerns. In contrast, we have considered model privacy and auction privacy issues in the design of the incentive mechanism. Moreover, the non-cooperation relationship between MSPs makes the design of auction mechanisms under a scenario of imperfect information. Therefore, the fairness and practicability of the auction mechanism of UGC need to be holistically studied.

2.2 Blockchain and Federated Learning in Metaverse

Blockchain is an essential infrastructure for the decentralized Metaverse ecosystem [53], which ensures security management and access control [12] for UGC with properties of decentralization, tamper-proof, and trustworthiness [13]. A review [11] discussed the Metaverse based on blockchain from the technical point of view and put forward some promising directions to innovate the usage of blockchain in Metaverse applications. Yang et al. [55] discussed how blockchain-empowered artificial intelligence (AI) technologies in the three-dimensional (3D) virtual worlds. Fan et al. [10] 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 mobile devices. Suhail et al. [45] proposed the usage of blockchain to target key challenges of untrustworthy data transmission and fault diagnosis in DT systems. However, there are few studies 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 [53], which efficiently assists in executing intensive computation on many edge devices of MUs. Chen et al. [4] designed a collaborating mobile edge computing paradigm with FL for AR applications. Moreover, there are some research works focused on FL-based digital twins. Lu et al. [33] utilized FL to construct the digital twin models for IoT devices and bridge the gap between the physical system and digital space in digital twin edge networks (DITENs). Lu et al. [34] further connected digital twins and wireless networks by the digital twin wireless networks (DTWN), in which real-time data signals and results can be migrated to the IoT edge devices. In terms of FL model utility, Zhang et al. [59] 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 [28] verified the ownership of FL models by watermarks embedded into the model. However, 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 auction mechanisms need to be investigated in-depth.

3 SYSTEM MODEL

In the Metaverse service, the MUs interact with the virtual world via some intelligent edge devices with an incredible amount of digital content created, i.e., UGC. In order to protect the ownership of creators, UGC can be minted to NFT via blockchain for collecting, trading, and accessing. The buyers can bid for the NFT with access right through digital currency based on blockchain. In this context, we focus on one novel type of UGC in the form of an FL global model, which can be minted as FL-NFT by a decentralized autonomous organization termed MU-DAO. In this section, we propose an FL-NFT auction model and formulate an FL cost-benefit framework in the process of FL-NFT minting.

3.1 FL-NFT auction model based on blockchain

We consider an FL-NFT auction model based on blockchain with N Metaverse users (MUs) labeled as $\mathcal{U} = \{U_1, U_2, \ldots, U_N\}$ and M Metaverse service providers (MSPs) labeled as $\mathcal{P} = \{P_1, P_2, \ldots, P_M\}$. All MUs are candidates for organizing a decentralized autonomous organization (i.e., MU-DAO) voluntarily, which can perform local model training and aggregate model parameters by a smart contract for a given period T. FL global models as one type of UGC can be minted as FL-NFT via blockchain. MSPs can bid for the FL-NFT to subsidize the computing resources cost and improve the user immersive experience to subside data contribution for heterogeneous edge devices of MUs, such as AR glasses and VR head-mounted devices (HMDs). 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 $L(\cdot)$ [60] 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 $L(\cdot)$ under budget constraints as

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

$$s.t. \sum_{i=1}^{N} C_i \leq \sum_{j=1}^{M} B_j, \tag{2}$$

where C_i is the cost of computing resources and data contribution for U_i, and B_j is the subsidizing budget of P_j.

The proposed PMS-AM system model based on blockchain consists of three phases: FL model training, FL-NFT minting, and FL-NFT auction, as shown in Fig. 2. In the FL model training phases, MUs can adjust the investment

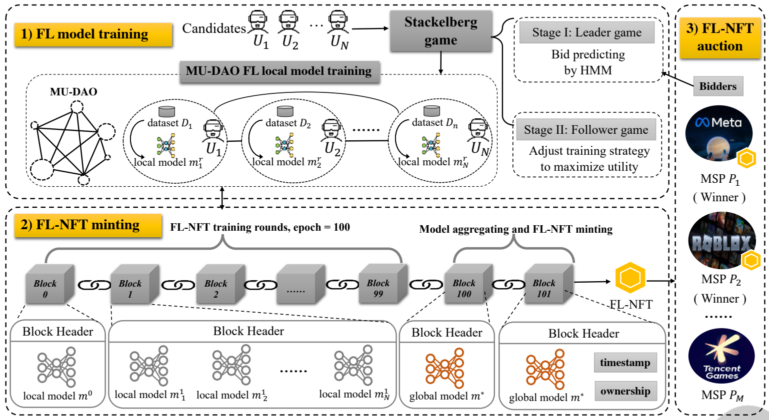


Fig. 2. The proposed PMS-AM system model based on blockchain. 1) FL model training process by Stackelberg game. 2) FL-NFT minting process based on blockchain 3) MSPs bid for FL-NFT by auction mechanism.

of resources in local model training and privacy budget based on the Stackelberg game, in which the backward induction is utilized to derive an equilibrium solution. In the FL-NFT minting phases, the smart contracts serve the role of the aggregator to generate FL-NFT and mint FL-NFT in the form of an FL global model by consensus within MU-DAO. In the FL-NFT auction phase, the HMM assists MSPs in choosing rational bidding strategies according to historical bids and an auction contract determines multiple winners with access priority according to sealed bids offered by MSPs.

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 imperfect information Stackelberg game (IISG). MU-DAO initializes the FL model parameters according to the chosen machine learning model and broadcasts them to MUs which begins local model training. The MU-DAO aggregates local models of MUs by a smart contract, which can encode by programming language (e.g., solidity) in advance according to the model aggregation algorithm, such as FedAvg [29], FedSim [40], FedAdp [37], FedSGD [5]. The smart contract distributes the t-th round model parameter m^t to MUs, which can adopt the mini-batch stochastic gradient descent algorithm [36] to update local model parameters as

$$\mathbf{g}\left(m_i^t, b_i\right) = \frac{1}{|b_i|} \sum_{l=1}^{|b_i|} \frac{\partial L\left(f\left(m_i^{t-1}, x_l\right), y_l\right)}{\partial m_i^{t-1}}, \tag{3}$$

where b_i is the mini-batch data sample, U_i updates local model parameters by $m_i^t = m_i^{t-1} - \gamma \cdot \mathbf{g}(m_i^{t-1}, b_i)$. The model training process repeats until the global model converges and FL global model m^* is generated. In order to protect the privacy of intermediate parameters, differential privacy [9] is utilized to disturb the gradient parameters before sharing in MU-DAO. We adopt Laplace noise to disturb gradient parameters $\mathbf{g}(m_i^t, b_i)$ as

$$\widetilde{\mathbf{g}}\left(m_i^t, b_i\right) = \mathbf{g}\left(m_i^t, b_i\right) + < Lap\left(\mu, \frac{\Delta f}{\epsilon_i}\right) >, \tag{4}$$

where μ is the location parameters, and $\frac{\Delta f}{\epsilon_i}$ is the scale parameters of Laplace distribution, Δf is the local sensitivity of noise, ϵ_i is the privacy budget set by U_i.

Table 1. Main Notations and Definitions

Notation	Definition
m^*	The model parameter of FL-NFT
m_i^t	The model parameter of U_i in t-th local iteration
$\tilde{\mathbf{g}}$	The perturbed gradient of the local model
ζ	The capacitance parameter
θ_i	The device memory of U_i
ξ_i	The average memory consumption ratio of U_i
C_i^c	The computation cost factor of U_i
C_i^p	The privacy cost factor of U_i
C_i	The total cost of U_i
$Q_j^{m^*}$	The model quality satisfaction of P_j
$F_j^{m^*}$	The model freshness satisfaction of P_j
b_j	The bid offered by MSP P_j
Φ_i	The utility of U_i in FL-NFT auction
Ψ_j	The utility of P_j in FL-NFT auction

2) FL-NFT minting

When FL global model m^* is generated, the smart contracts serve as the minters to collect the model parameters m^*, the minting timestamp τ_{m^*}, and the public key of MU-DAO, etc. Then, miners pack this information to a file named fl-nft.js, which is recorded in the blockchain to ensure that FL-NFT is truly 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. The MSPs (i.e., buyers of FL-NFT) can get the access priority of FL-NFT to improve the user experience in Metaverse services.

3) FL-NFT auction

MSPs offer bids to the blockchain-based auction platform, where the multi-winner sealed auction mechanism is implemented in the auction smart contract to realize automatic auction execution. The auction smart contract as the auctioneer determines multiple winners according to bids of MSPs, where the higher the bid, the higher access priority of FL-NFT can be given until the auction clock expires. In Section 5, we adopt HMM to assist MSPs in choosing rational bidding strategies according to historical bids, achieving individual rationality and incentive compatibility. Due to heterogeneity between MUs in computing, storage, communication resources, and data quality, there are free-rider and unfairness issues within MU-DAO. Therefore, it is necessary to trade off the cost and benefit to encourage more MUs to participate in MU-DAO fairly. We formulate the FL cost-benefit framework in Section 3.2 and list notations and definitions used in this paper in Table 1.

3.2 FL Cost-benefit Framework of the Metaverse Users

Assisted by edge computing, rendering tasks in the Metaverse could be offloaded to VR devices of MUs in edge networks. MUs must consume computing resources to train FL local models, such as CPU and memory. In addition, MSPs are required to collect personal data from MUs to predict user behavior and social relationships. Therefore, we mainly consider the computation and privacy costs. Based on the quantification of the above two cost elements, the cost function of MU U_i to perform the FL training task can be expressed as

$$C_i = C_i^c k_i + C_i^p \epsilon_i, \forall k_i \in \mathbb{Z}^+, \forall \epsilon_i \in \mathbb{R}^+, \tag{5}$$

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 numbers of local iterations and the differential privacy budget [9], respectively.

- *Computation cost factor C_i^c:* The CPU performance of U_i for local model training is f_i (i.e., CPU clock frequency), ξ_i is the average memory occupation ratio in one iteration, θ_i is the device memory, and the memory occupation for local model training is $\xi_i\theta_i$. Based on the secondary energy consumption model of CPU [47], the per unit computation cost of local model iteration can be defined as

$$C_i^c = \alpha\zeta z_i s_i f_i^2 + (1-\alpha)\,\xi_i\theta_i, \tag{6}$$

where α is the computation cost adjustment factor, ζ is the effective capacitance [20], 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 [32], we adopt gradient-norm to measure privacy preference. Thus, the per unit cost of privacy disclosure C_i^p can be defined as

$$C_i^p = \beta \ln\left(1 + \left\|\widetilde{\mathbf{g}}\left(m_i^t, b_i\right)\right\|\right), \tag{7}$$

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. Therefore, MU-DAO prefers to recruit more MUs with larger privacy budgets to improve the quality of FL-NFT, which increases the privacy cost.

Note that we consider a general cost model without constraint on the type of blockchain. Gas fees need to be considered an optional cost factor for Ethereum. In the FL-NFT auction market, the MSPs determine the bidding strategies for FL-NFT by satisfaction evaluation. MUs need to decide on the training strategies for FL-NFT by adjusting their local iterations and privacy budget to maximize their benefits. Unlike the traditional FL incentive mechanism, in blockchain-driven Metaverse, both the FL model quality and immersive experience of MUs need to be considered to achieve a holistic evaluation of the satisfaction of FL-NFT. With the above consideration, 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^* minted by an MU-DAO, denoted as

$$\varphi_j^{m^*} = \left(Q_j^{m^*}\right)^{e_j^Q} + \left(F_j^{m^*}\right)^{e_j^F} = \left(Q_j^{m^*}\right)^{\lambda} + F_j^{m^*}, \tag{8}$$

$$s.t.\ \lambda = \frac{e_j^Q}{e_j^F} > 0, 0 < e_j^Q \le 1, 0 < e_j^F \le 1, e_j^Q + e_j^F = 1, \tag{9}$$

where e_j^Q and e_j^F are demand price elasticity of model quality $Q_j^{m^*}$ and freshness $F_j^{m^*}$ determined by P_j, respectively [4].

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, resulting in higher bids. Therefore, the satisfaction contribution of MUs to the FL-NFT in model quality and freshness also needs to be measured by an appropriate metric. 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 these two satisfaction contributions for U_i in detail as follows:

- *The model quality contribution θ_i^Q:* For U_i, the model quality contribution is determined by its local model 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 [6] as $H_i =$

[4]The parameters $e_j^Q = 1$ 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.

$-\sum_{i=l}^{d} y_l logf(x_l)$, where $f(x_l)$ is the predicted value by the function $f(\cdot)$ and y_l is the labeled value. Therefore, θ_i^Q can be denoted as

$$\theta_i^Q = \frac{\mu_0|\mathcal{D}_i|}{\mu_1 - \frac{1}{R}\sum_{i=1}^{R} y_i logf(x_i)}, \tag{10}$$

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 [29]. In this paper, u_0 represents the number of model hidden layers, and u_1 represents the number of model output layers, R represents the total round of U_i participating 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 [1, 58], a metric of the age of information (AoI) can be used to denote the duration of MUs participating in FL-NFT minting. For U_i, the duration T_i mainly includes the time of training T_i^m, uploading T_i^l and consensus T_i^c, which can be denoted as

$$T_i = T_i^m + T_i^l + T_i^c, \tag{11}$$

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, yet resulting in a longer training time for U_i, i.e., the numbers of local iterations. Furthermore, the model parameters and other necessary information are broadcasted in MU-DAO with a communication delay, which is related to the transmission data size d_i and 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 algorithms. A small value of T_i indicates a fresher local model, as per [31], the model freshness contribution θ_i^F can be defined as

$$\theta_i^F = log(1/T_i), \tag{12}$$

We assume that under a rational auction market, U_i can get the 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

$$\delta_{ij} = q_j\left(Q_j^{m^*}\right)^{\lambda}\tau_i^Q + f_j F_j^{m^*}\tau_i^F, \tag{13}$$

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

4 STRATEGY OPTIMIZATION BASED ON STACKELBERG GAME

In this section, we construct an imperfect information Stackelberg game (IISG) [49] to trade off the cost and benefit by optimizing the training strategies of MUs and bidding strategies of MSPs. In the first stage, the bidding strategies of MSPs are determined by the satisfaction with model quality and freshness. In the second stage, MUs adjust the numbers of local iterations and privacy budgets according to the bidding strategy, which can ensure individual rationality and incentive compatibility. In the practical auction market, the MSPs demanding the same FL-NFT are non-cooperative relationships, so the bidding strategies of competitors are hidden from MSPs due to the fairness and privacy requirement.

4.1 Stackelberg Game Formulation

In the game decision, we assume that MSPs and MUs are all rational individuals, in which MUs can make the decision in a 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. We construct the IISG to analyze the optimal strategies of MUs and MSPs as below.

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 utility function is usually a concave function with the property of decreasing marginal utility. Therefore, the optimization problem for MU U_i within a given game decision period T can be formulated as follows:

Problem 1. The utility maximization problem for MU U_i in Stage II as

$$\max \Phi_i \left(\boldsymbol{K}_i, \boldsymbol{E}_i\right) = \sum_{j=1}^{M} \delta_{ij} \left(h\left(k_{ij}\right) + h\left(\epsilon_{ij}\right)\right) - C_i, \tag{14}$$

$$\begin{aligned} s.t.\ C1 &: C_i \leq \sum_{j=1}^{M} \delta_{ij} \left(h\left(k_{ij}\right) + h\left(\epsilon_{ij}\right)\right), \forall j, \\ C2 &: \frac{k_{ij}}{\zeta z_i s_i f_i^2} + \frac{z_i s_i}{b_i} \leq T, \end{aligned} \tag{15}$$

where $h(k_{ij}) + h(\epsilon_{ij})$ indicates the benefit of MUs enjoying the Metaverse service, $h(x)$ is defined by the σ-fair function adopted in [51, 52] defined as $h(x) = \frac{1}{1-\sigma} x^{1-\sigma}$ [5], 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 total bidding reward of U_i exceeds the cost. $C2$ expresses that the decision time of U_i is limited and cannot exceed given the game decision period T. Upon observing the bidding strategies offered by the MSPs, each MU U_i determines the optimal training strategies $(\boldsymbol{K}_i^*, \boldsymbol{E}_i^*)$.

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 of the FL-NFT, which are related to 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 optimization problem for MSP P_j can be formulated as follows:

Problem 2. The utility maximization problem for MSP P_j in Stage I as

$$\max \Psi_j \left(\boldsymbol{Q}_j, \boldsymbol{F}_j\right) = \sum_{i=1}^{N} \left(q_{ij} w_{ij}^{q} + f_{ij} w_{ij}^{f} - \delta_{ij}\right), \tag{16}$$

$$\begin{aligned} s.t.\ C1 &: \sum_{i=1}^{N} \left(q_{ij} + f_{ij}\right) \leq B_j, \forall j, \\ C2 &: t_j \leq T, \forall j, \end{aligned} \tag{17}$$

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 the decision time is limited. The winning probability for MSP is relevant to the proportion of the total bid in general, which

[5]The function $h(x)$ 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 to the Metaverse service.

can be denoted as $w_{ij}^{q} = \frac{q_{ij}}{\left(q_{ij}+\sum_{ij',j'\neq j}^{m} q_{ij'}\right)}$ and $w_{ij}^{f} = \frac{f_{ij}}{\left(f_{ij}+\sum_{ij',j'\neq j}^{m} f_{ij'}\right)}$ [6]. Due to the non-cooperative relationship among MSPs, the actual bids of other competitors are non-public information. At the beginning of the FL-NFT auction, MSP P_j can observe the bids of other competitors in the historical auction to determine initial bids. Then, MSPs can leverage HMM to obtain the most likely bidding strategies of other competitors.

3) Stackelberg equilibrium

Stackelberg equilibrium is an optimal solution where the utilities of the followers can be maximized by choosing the best responses given the optimal strategies of leaders. **Problem 1** and **2** together form an IISG with the objective of finding the Stackelberg equilibrium in Stage I and Stage II, i.e., the solution at which the MUs' utilities are maximized by adjusting training strategies given that the MSPs offer their optimal bidding strategies. We consider a multi-MU and multi-MSP game, where each MU U_i has a finite set of training strategy $\mathbf{A}_i^t \triangleq < \boldsymbol{K}_i, \boldsymbol{E}_i >$, MSP P_j has a finite set of bidding strategy $\mathbf{A}_j^b \triangleq < \boldsymbol{Q}_j, \boldsymbol{F}_j >$, and $\mathbf{A}_i^t \times \mathbf{A}_j^b \rightarrow \mathbb{R}$.

Definition 1: The Stackelberg equilibrium for IISG is an optimal training strategy $< \boldsymbol{K}_i^*, \boldsymbol{E}_i^* >$ for MU U_i given a bidding strategy $< \boldsymbol{Q}_j^*, \boldsymbol{F}_j^* >$ for MSP P_j such that:

$$\Phi_i(\boldsymbol{K}_i^*, \boldsymbol{E}_i^*) \geq sup\{\Phi_i(\boldsymbol{K}_i, \boldsymbol{E}_i)\}, k_{ij} \in \mathbb{Z}^+, \epsilon_{ij} \in \mathbb{R}^+, \forall i, \tag{18a}$$

$$\Psi_j(\boldsymbol{Q}_j^*, \boldsymbol{F}_j^*) \geq sup\{\Psi_j(\boldsymbol{Q}_j, \boldsymbol{F}_j)\}, q_{ij} \in \mathbb{R}^+, f_{ij} \in \mathbb{R}^+, \forall j. \tag{18b}$$

Note that the Stackelberg equilibrium defines a situation where utility maximization for MUs and MSPs is reached with the adjustment of action strategies. Condition (18a) means that MUs' training strategy is an optimal response to MSPs' bidding strategy at each game decision period of the IISG. Condition (18b) implies that the expected utility generated by the bidding strategy of MSPs is optimal under the constraint that the training strategies of MUs must always be an optimal response. In the FL-NFT auction market, given the bidding strategies of MSPs, the MUs act as followers to optimize their training strategies to realize the Stackelberg equilibrium. To investigate the Stackelberg equilibrium of IISG, we adopt the backward induction in the following subsection to address the **Problem 1** and **2**.

4.2 Solving Stackelberg Equilibrium of IISG

In this subsection, we solve the Stackelberg equilibrium of IISG by the backward induction, 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 [42].

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 numbers of local iterations and privacy budget.*

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

$$H(\Phi_i) = \begin{bmatrix} \frac{\partial^2 \Phi_i}{\partial \boldsymbol{K}_i^2} & \frac{\partial^2 \Phi_i}{\partial \boldsymbol{K}_i \partial \boldsymbol{E}_i} \\ \frac{\partial^2 \Phi_i}{\partial \boldsymbol{E}_i \partial \boldsymbol{K}_i} & \frac{\partial^2 \Phi_i}{\partial \boldsymbol{E}_i^2} \end{bmatrix} = diag(H_{ij}^K, H_{ij}^E), \tag{19}$$

and

$$H_{ij}^K = \left[\frac{\partial^2 \Phi_i(\boldsymbol{K}_i, \boldsymbol{E}_i)}{\partial k_{ij} \partial k'_{ij}}\right]_{j,j' \in \{1,2,\ldots,M\}} = -diag(h_{i1}^k, h_{i2}^k, \ldots h_{ij}^k) < 0, \tag{20}$$

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

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

$$H_{ij}^E = \left[\frac{\partial^2 \Phi_i(\boldsymbol{K}_i, \boldsymbol{E}_i)}{\partial \epsilon_{ij} \partial \epsilon_{ij'}}\right]_{j,j' \in \{1,2,\ldots,M\}} = -diag(h_{i1}^{\epsilon}, h_{i2}^{\epsilon}, \ldots h_{ij}^{\epsilon}) < 0, \tag{21}$$

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

$$(\boldsymbol{K}_i^*, \boldsymbol{E}_i^*) = [(\sqrt[-\sigma]{C_i^c/\delta_{ij}}, \sqrt[-\sigma]{C_i^p/\delta_{ij}})]. \tag{22}$$

Since the numbers of local iterations of MUs are within the positive integer space $\mathbb{Z}^+$. MUs can adjust the numbers of local iterations $\boldsymbol{K}_i^*$ to $\boldsymbol{K}_i^{a*}$ through the Eq.(23).

$$\boldsymbol{K}_i^{a*} = \lceil \boldsymbol{K}_i^* \rceil, \tag{23}$$

where $\lceil x \rceil$ is the integer function, denote that $\lceil x \rceil = min\{\varsigma \in \mathbb{Z}, \varsigma \leq n\}$. So far, we have solved the Stackelberg equilibrium in **Problem 1**.

We further analyze the equilibrium existence and uniqueness for the optimal bidding strategies of MSPs through **Theorem 2**. Given the training strategies of MUs in **Problem 1**, each MSP P_j adjusts the bidding strategies to maximize its utilities Ψ_j. In the first game period, the MSP P_j is able to offer the bidding decision by the predicted satisfaction for the FL-NFT due to the feature of first-moving. By analyzing any utility Ψ_i for MSP P_j given in Eq.(16) and condition given in Eq.(17), 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 Hessian matrix of $\Psi_j(\boldsymbol{Q}_j, \boldsymbol{F}_j)$ with respect to bidding strategies $\boldsymbol{Q}_j$ as

$$H(\Psi_j) = \begin{bmatrix} \frac{\partial^2 \Psi_j}{\partial \boldsymbol{Q}_j^2} & \frac{\partial^2 \Psi_j}{\partial \boldsymbol{Q}_j \partial \boldsymbol{F}_j} \\ \frac{\partial^2 \Psi_j}{\partial \boldsymbol{F}_j \partial \boldsymbol{Q}_j} & \frac{\partial^2 \Psi_j}{\partial \boldsymbol{F}_j^2} \end{bmatrix} = diag(H_{ij}^Q, H_{ij}^F), \tag{24}$$

and

$$H_{ij}^Q = \left[\frac{\partial^2 \Psi_j(\boldsymbol{Q}_j, \boldsymbol{F}_j)}{\partial q_{ij} \partial q_{i'j}}\right]_{i,i' \in \{1,2,\ldots,N\}} = -diag(h_{i1}^q, h_{i2}^q, \ldots h_{ij}^q) < 0, \tag{25}$$

where

$$h_{ij}^q = \frac{w_{ij}^q}{q_{ij}} + \frac{(\sum_{i',i'\neq i}^n q_{i'j}) + \sum_{i',i'\neq i}^n q_{i'j}}{(q_{ij} + \sum_{i',i'\neq i}^n q_{i'j})^3}. \tag{26}$$

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

$$H_{ij}^F = \left[\frac{\partial^2 \Psi_j(\boldsymbol{Q}_j, \boldsymbol{F}_j)}{\partial f_{ij} \partial f_{i'j}}\right]_{i,i' \in \{1,2,\ldots,N\}} = -diag(h_{i1}^f, h_{i2}^f, \ldots h_{ij}^f) < 0, \tag{27}$$

where

$$h_{ij}^f = \frac{w_{ij}^f}{f_{ij}} + \frac{(\sum_{i',i'\neq i}^n f_{i'j}) + \sum_{i',i'\neq i}^n f_{i'j}}{(f_{ij} + \sum_{i',i'\neq i}^n f_{i'j})^3}. \tag{28}$$

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

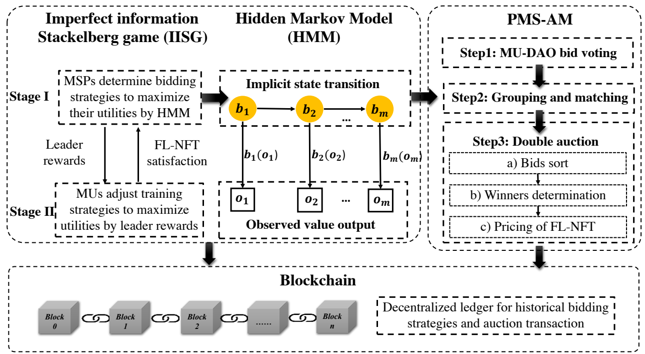


Fig. 3. The structure of HMM assisted IISG for FL-NFT auction in the blockchain-driven Metaverse.

partial derivative of $\Psi_j(\boldsymbol{Q}_j, \boldsymbol{F}_j)$, we obtain the equilibrium solution as

$$(\boldsymbol{Q}_j^*, \boldsymbol{F}_j^*) = [(\sqrt{\frac{\Delta_q^2 + \Delta_q}{\left(Q_j^{m^*}\right)^{\lambda} + 1}} - \Delta_q, \sqrt{\frac{\Delta_f^2 + \Delta_f}{F_j^{m^*} + 1}} - \Delta_f)], \tag{29}$$

where

$$\begin{cases} \Delta_q = \sum_{i',i' \neq i}^{n} q_{i'j} \\ \Delta_f = \sum_{i',i' \neq i}^{n} f_{i'j} \end{cases}. \tag{30}$$

So far, we verify the existence and uniqueness of Stackelberg equilibrium in **Problem 1** and **2**, indicating that every MSP has a unique optimal solution of the bidding strategy to maximize its utilities given the training strategies of MUs. Therefore, the Stackelberg equilibrium can be achieved in the proposed auction game model 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, and none of them tends to adjust their strategies to gain higher utilities.

5 PRIVACY-PRESERVING MULTI-WINNER SEALED-BID AUCTION MECHANISM

According to the Stackelberg equilibrium proved in Section 4, it is possible to obtain an optimal solution to optimize the training strategies of MUs and bidding strategies of MSPs in IISG. However, the stable Stackelberg equilibrium faces the following challenges practically. 1) MSPs who demand FL-NFT are averse to disclosing their actual bids to competitors due to the non-cooperative relationship. 2) MSPs are unable to predict the bidding strategies of competitors in IISG accurately. 3) The public goods attribute of FL-NFT may cause insufficient fairness in the single-side auction mechanism, such as British and Dutch auctions. To address the above challenges, we formulate a privacy-preserving multi-winner sealed-bid auction mechanism (PMS-AM) to determine the winning MSPs, where each MSP acts as the individual agent to predict the bidding strategies of competitors by HMM.

5.1 MSP bid prediction based on HMM

In an FL-NFT auction market, the MSPs as bidders are independent and competitive, and they are reluctant to disclose their real bids to competitors generally. In order to build a privacy-preserving auction mechanism, HMM [2] is adopted to predict bids of competitors, in which the historical bidding sequence recorded in blockchain can be used to predict the bids of MSPs. The structure of HMM-assisted IISG for FL-NFT auction in the blockchain-driven Metaverse is shown in Fig. 3. Specifically, HMM assists MSPs in computing the benefits from the auction, where historical bidding strategies of MSPs are recorded on the distributed ledger transparently. In Stage I of IISG, MSPs can determine their subsequent bidding strategies according to the predicted bids of other competitors and their satisfaction with FL-NFT. In Stage II of IISG, MUs can adjust their training strategies according to the bidding reward from MSPs to maximize utilities.

In IISG, MSPs need to compute their winning probability to evaluate the auction benefit. The HMM can assist MSP P_j in predicting the bids of competitors. In order to simplify the analysis, we combine the model quality bid q_j and freshness bid f_j into one symbol b_j for description. For any MSP P_j, HMM can be described by a 5-tuple:$< \Omega_X, \Omega_O, I, A, B >$, including two finite state sets, i.e., state set Ω_X and observation set Ω_O, and three probability matrices, i.e., I, A, B.

- $\Omega_X = \{b_1, b_2, \ldots, b_Q\}$ is the finite state bids set offerd by MSP P_j within game decision period T, where b_i presents the bids offered by MSP P_j for FL-NFT m^* in the i-round game decision.
- $\Omega_O = \{o_1, o_2, \ldots, o_K\}$ is a sequence of K historical observation bids of MSPs, where o_i is derived from historical bids recorded on blockchain at time t.
- $I = \{I_1, I_2, \ldots, I_Q\}$, is the initial state probability distribution over states Ω_X, and each I_i is the probability that Markov chain start from bid b_i. Some state b_i may have $I_i = 0$, meaning that b_i cannot be the initial states.
- $A = \{a_{11}, \ldots, a_{ij}, \ldots, a_{QQ}\}$, where $a_{ij} = p(X_{t+1} = b_j | X_t = b_i)$ is the transition probability matrix, each a_{ij} is the probability of moving from bid b_i to bid b_j, which satisfies $\sum_{j=1}^{N} a_{ij} = 1, \forall i$.
- $B = \{b_1(o_1), \ldots, b_i(o_k), \ldots, b_N(o_K)\}$ is a sequence of observation likelihoods or emission probabilities, and $b_i(o_k) = p(O_t = o_k | X_t = b_i)$ denotes the probability of an observation o_k being generated from a state b_i.

In the proposed auction model, Ω_X and Ω_O are independent and $p(O_t = o_k) > 0$ is satisfied. We can obtain the following conditional probability as

$$p(X_{t+1} = b_j | O_{t+1} = o_{t+1}) = \frac{p\{X_{t+1} = b_j, O_{t+1} = o_{t+1}\}}{p(O_{t+1} = o_{t+1})}. \tag{31}$$

Let $p\{X_{t+1} = b_j, O_{t+1} = o_{t+1}\} = \eta_{t+1}(b_j, o_{t+1})$. We can derive the likelihood of bid b_j given the observation o_{t+1} by Eq.(32) according to the forward algorithm [56].

$$\begin{aligned}
\eta_{t+1}(b_j, o_{t+1}) &= p(b_j | o_{t+1}) \sum_{b_i \in X} \eta_{t+1}(b_j, o_{t+1}) \\
&= \sum_{b_i \in X} p(X_t = b_i, O_t = o_t, X_{t+1} = b_j, O_{t+1} = o_{t+1}) \\
&= \sum_{b_i \in X} \eta_t(b_j, o_t) p\{X_{t+1} = b_j | X_t = b_i\} p\{O_{t+1} = o_{t+1} | X_{t+1} = b_j\}.
\end{aligned} \tag{32}$$

Substituting $p\{X_{t+1} = b_j | X_t = b_i\} = a_{ij}$ and $p\{O_{t+1} = o_{t+1} | X_{t+1} = b_i\} = b_i(o_{t+1})$ into Eq.(32) we have

$$\eta_{t+1}(b_j, o_{t+1}) = \sum_{b_i \in X} \eta_t(b_i, o_t) a_{ij} b_i(o_{t+1}). \tag{33}$$

Therefore, MSPs can obtain the probability of all the possible bids offered by the competitors and determine the maximum probability b_i to compute the winning probability. In our work, MSPs operate HMM based on the record in blockchain to predict bids of competitors and construct the imperfect information Stackelberg game (IISG) to optimize bidding strategies. This determines that the auction process protects the privacy of bidding information under the current auction market state and achieves the Stackelberg equilibrium.

5.2 Multi-Winner and Payment Scheme Determination

We investigate the two-side online auction interactions among MU-DAOs and MSPs in the blockchain-driven Metaverse, explicitly taking the public goods[7] of FL-NFT into account. The proposed PMS-AM defines a multi-winner determination and a payment scheme based on McAfee's double auction [35] and second price auction to achieve individual rationality and incentive compatibility. To minimize the risk of privacy disclosure in the process of FL-NFT auction, MSPs can offer encrypted bidding information to the auctioneer (i.e., auction smart contract). After digital signature verification, the auctioneer decrypts the information with a private key and determines the auction results.

In an FL-NFT auction market, we suppose that there are multiple sellers (i.e., MU-DAOs), denoted by $\mathcal{U}_s = \{U_1^s, U_2^s, \ldots, U_H^s\}$ and multiple buyers (i.e., MSPs), denoted by $\mathcal{P}_b = \{P_1^b, P_2^b, \ldots, P_M^b\}$. Different MU-DAOs are responsible for minting different FL-NFTs $\mathcal{F} = \{F_1, F_2, \ldots, F_H\}$. The FL-NFT auction mechanism PMS-AM $=< \mathcal{U}_s, \mathcal{P}_b, \mathcal{F} >$ is composed of MU-DAO space $\mathcal{U}_s$, MSP space $\mathcal{P}_b$, FL-NFT space $\mathcal{F}$. For any MU $U_i \in U_h^s$ participate in the FL-NFT F_h minting task, the training strategies $\mathbf{A}_i^t \triangleq < \boldsymbol{K}_i, \boldsymbol{E}_i >$ contains the numbers of local iterations $\boldsymbol{K}_i$ and privacy budget $\boldsymbol{E}_i$, all of which are adjusted to realize the utility Φ_i maximization in Stage II of IISG. Meanwhile, MSP P_j bidding for F_h chooses an optimal bidding strategy $\mathbf{A}_j^b \triangleq < \boldsymbol{Q}_j, \boldsymbol{F}_j >$, which contains model quality bid $\boldsymbol{Q}_j$ and model freshness bid $\boldsymbol{F}_j$, to maximize their utility Ψ_j in the stage I of IISG. After multiple rounds of strategy optimization, the PMS-AM allows MU-DAOs and MSPs to determine a reasonable clearing price of FL-NFT, which consists of the following three phases:

1) MU-DAO bid voting

In the FL-NFT F_h minting process, we suppose the MU-DAO U_h^s recruits all candidate MUs with surplus resources to train the FL global model. Considering the public goods nature of FL-NFT, the reasonable price of F_h is difficult to determine by uniform direct pricing. Therefore, we apply the widely adopted majority voting scheme [16] to express the diversified price preferences of MUs for F_h. Specifically, MUs in U_h^s can report an asking bid proposal of F_h, formed as a bid set $\mathcal{B}_h^u = \{b_1^u, b_2^u, \ldots, b_N^u\}$ according to their expected benefits denoted in Eq.(13). Then, U_h^s executes bid voting for each U_i's reported bid with majority agreement from the remaining MUs, denoted as $v_{i'}^u \triangleq \{0, 1\}$ [8]. The MU-DAO retains the asking bids supported by more than half of the MUs. If more than half of MUs in MU-DAO approve the b_i^u, U_i will receive a consistency benefit $b_i^u = \sum_{j=1}^M \delta_{ij}$, otherwise, $b_i^u = 0$. Note that δ_{ij} is only broadcast in the private network of MU-DAO. Therefore, MSPs cannot retrieve the bidding proposal information of MUs. More specifically,

$$b_i^u = \begin{cases} \sum_{j=1}^M \delta_{ij}, & if \ \ \sum_{i'=1}^N v_{i'}^u \geq \frac{N}{2}, \forall i' \neq i, \\ 0, & if \ \ \sum_{i'=1}^N v_{i'}^u < \frac{N}{2}, \forall i' \neq i. \end{cases} \tag{34}$$

After all MUs complete the bid voting, the U_h determines the asking price of F_h, which is marked as $B_h = \sum_{i=1}^N b_i^u$.

2) Grouping and matching

The FL-NFT auction market is constructed by a blockchain-based decentralization platform, where a smart contract as auctioneer broadcasts the relevant information of FL-NFT, including ownership, asking bid and service content keywords, etc., to MSPs registered on the platform. The auction smart contract matches the MSPs with the FL-NFTs owned by different MU-DAOs based on the required sequence. Suppose a grouping algorithm is executed to generate an FL-NFT seller group set $\mathbf{G}^s$ and a buyer group set $\mathbf{G}^b$. When a seller group $\mathbf{g}_i^s \in \mathbf{G}^s$ satisfies the requirement of buyers in group $\mathbf{g}_j^b \in \mathbf{G}^b$, χ is denoted the matching relationship, we have

[7] In economics, a public good is a good that is both non-excludable and non-rivalrous.

[8] If $U_{i'}$ approve of the asking bid of U_i, then $v_{i'}^u = 1$, otherwise $v_{i'}^u = 0$.

$\chi(\mathbf{g}_i^s) = \mathbf{g}_j^b$ and $\chi(\mathbf{g}_j^b) = \mathbf{g}_i^s$. If the number of successfully matched sellers and buyer groups is D, then we have $D \leq min\{|\mathbf{G}^s|, |\mathbf{G}^b|\}$.

3) Double auction

In the FL-NFT auction market, MSPs and MU-DAOs can be viewed as independent buyers and sellers, respectively. McAfee's double auction mechanism [2] can be leveraged by the auction smart contract to determine multi-winner and payment schemes in a distributed manner based on blockchain.

a) Bids sorting: The auction smart contract sorts bids of matched seller group $\mathbf{g}_i^s$ in increasing order, and sorts bids of matched buyer group $\mathbf{g}_j^b$ in descending order as follows:

$$v_{i1}^s \leq v_{i2}^s \leq \cdots \leq v_{iD}^s, \tag{35a}$$

$$v_{j1}^b \geq v_{j2}^b \geq \cdots \geq v_{jD}^b. \tag{35b}$$

b) Winners determination: The winners are determined by finding the largest k that satisfies $v_{jk}^b \geq v_{ik}^s$ from the two bids order, then the first k MSPs are added into the candidate winner sets $\mathbf{g}_i^{b(w)}$. The MU-DAO with the smallest sell-bid wins. If $\mathbf{g}_i^{b(w)} = \varnothing$, the MSPs and MU-DAOs need to offer new bids until the auction clock expires.

c) Pricing of FL-NFT: In order to encourage bidders to offer more realistic and truthful bids, we adopt the second-price auction to price the FL-NFT. In particular, the winning MU-DAO gets the next smallest sell bid as the price of FL-NFT. The winning MSPs give the next largest buy-bid to get the access right of FL-NFT F_h. Note that the higher the bid is, the higher the access priority of FL-NFT can be given. The price difference between the next largest buy-bid and the next smallest sell-bid is the profit of the auctioneer (i.e., auction smart contract). The MU U_i in winning MU-DAO can share the benefit according to its bid voting result, denoted by Eq.(34).

In practical trading scenario, the minting and auction process of FL-NFT involves primary market and secondary market. Specifically, FL-NFT can be minted and issued in primary market and then enters into the secondary market to perform circulation trading. As the most popular NFT secondary market, OpenSea supports three types of NFT pricing mechanisms, including direct pricing, auction, and package selling. Considering the characteristics of FL-NFT, we investigate the two-sided online auction interactions among sellers (i.e., MU-DAOs) and buyers (i.e., MSPs). In the FL-NFT minting process, MUs are motivated to participate in a decentralized autonomous organization (i.e., MU-DAO) to aggregate local models and mint FL-NFT. Due to the heterogeneity of MUs, we proposed PMS-AM to support MUs in expressing diversified price preferences and giving selling bids by majority voting agreement. Indeed, the price offered by MSPs will affect the auction result. In this regard, we formulate a classic McAfee's double auction mechanism to determine the winning MSPs, and a second-price auction is adopted to give the final price of FL-NFT. The auction result depends on the bids offered by MSPs and McAfee's double auction rules, which guarantee both the IR and IC property.

5.3 Economic properties Analysis

To ensure the effectiveness of the proposed PMS-AM, we analyze the following key economic properties, including individual rationality, incentive compatibility and budget balance.

Theorem 3. *The proposed PMS-AM scheme achieves individual rationality (IR).*

Proof. For each MU $U_i \in \mathcal{U}$, by observing the utility function in Eq.(14) and the constraint $C1$ in Eq.(15) we have $\Phi_i = \sum_{j=1}^{M} \delta_{ij} \left(h\left(k_{ij}\right) + h\left(\epsilon_{ij}\right)\right) - C_i \geq 0$. Thus, for each MU $U_i \in \mathcal{U}$, the utility $\Phi_i \geq 0$.

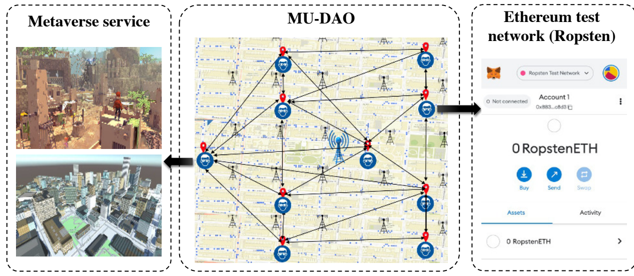


Fig. 4. The simulation scenario of MU-DAO is based on 10 tracepoints of Roblox Metaverse users.

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 $q_{ij} + f_{ij} \geq \delta_{ij}$. By combining the constraint $C1$ in Eq.(17) we have

$$\Psi_j = \sum_{i=1}^{N} \left(q_{ij} + f_{ij} - \delta_{ij}\right) \geq 0. \tag{36}$$

Thus, for each MSP $P_j \in \mathcal{P}$, the utility $\Psi_j \geq 0$. So, the proposed PMS-AM scheme achieves incentive rationality.

Theorem 4. *The proposed PMS-AM scheme achieves incentive compatibility (IC).*

Proof. In the phase of FL-NFT minting, the MUs optimal their training strategies $\mathbf{A}_i^t \triangleq < \boldsymbol{K}_i, \boldsymbol{E}_i >$ and MSPs optimal their bidding strategies $\mathbf{A}_j^b \triangleq < \boldsymbol{Q}_j, \boldsymbol{F}_j >$ 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 the PMS-AM, for each MSP P_j, it satisfies $E(\Psi_j(\boldsymbol{Q}_j^*, \boldsymbol{F}_j^*)) \geq E(\Psi_j(\boldsymbol{Q}_j, \boldsymbol{F}_j))$, and for each MU U_i it satisfies $E(\Phi_i\left(\boldsymbol{K}_i^*, \boldsymbol{E}_i^*\right)) \geq E(\Phi_i\left(\boldsymbol{K}_i, \boldsymbol{E}_i\right))$. 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. So, the proposed PMS-AM scheme achieves incentive compatibility.

Lemma 1. *The proposed PMS-AM scheme achieves budget balance.*

Proof. The utilities of all MUs and MSPs are positive according to Theorem 3. Then, the budget is the sum of the utilities of all MSPs $\sum_{j=1}^{M} \Psi_j \geq 0$. By combining the constraint $C1$ in Eq.(15) and McAfee's double auction, we have the profit of the auctioneer non-negative. So, the proposed PMS-AM achieves a budget balance.

6 SIMULATION AND EVALUATION

In this section, we conduct experimental simulations to evaluate the convergence performance of FL-NFT and verify the effectiveness of our proposed PMS-AM. We first compare the test accuracy of FL-NFT with four baselines regarding different learning training strategies. Then, we evaluate the effect of the auction and incentive, including the cost and utility of MU-DAO. Finally, we statistic the average FL-NFT minting time for MU-DAO completing PMS-AM.

6.1 Simulation Settings

- ***Setup***: We simulate an MU-DAO by recruiting 10 MUs to participate in FL-NFT training and minting. We define a $1000m \times 1200m$ area as a simulation scenario, in which 10 tracepoints of Roblox MUs are deployed. The tracepoints of Roblox are plotted by the matplotlib map toolkit and the simulation scenario as shown in Fig. 4.
- ***Environment***: We implement PMS-AM on 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. We use a

Table 2. 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	$\alpha = 0.3, \beta = 0.5, \xi_i = 0.5, \theta_i = 8$

crypto wallet (i.e., MetaMask[9]) to realize a blockchain-based auction smart contract, in which the auction transaction can be recorded on Ethereum test network Ropsten[10], in which proof-of-work (PoW) is used for consensus and users can hold RopstenETH for purchase of FL-NFT.

- ***Datasets***: Under the simulation scenario, the MNIST [25] and CIFAR-10 [23] datasets are divided equally into 10 MUs. The MNIST dataset $\mathcal{D}_M$ contains 60000 handwriting grayscale images from 1 to 10. The CIFAR-10 dataset $\mathcal{D}_C$ consists of 60000 color images into 10 classes. Both MNIST and CIFAR-10 datasets are divided into two sets: 50000 randomly selected training samples and the rest 10000 test samples.
- ***Models***: The neural networks select multi-layer perceptron (MLP) [39] and convolutional neural networks (CNN) [14] for model training, which can be aggregated by FedAvg [29] to update the model parameters. Each MU executes the mini-batch stochastic gradient descent algorithm [36] to optimize the local model and complete the cooperative training within MU-DAO. Both models use the rectified linear unit (ReLU) activation function.

Under the PMS-AM for FL-NFT designed in this paper, the convergence of the FL model quality at the same setting is compared. We adjust hyper-parameters for all datasets and models to the best result among 5 runs. All experiments are conducted based on a lightweight FL open source framework[11] as the benchmark, which sets the clients to participate in FL randomly. The specific experimental parameter settings are shown in Table 2.

6.2 Results and Analysis

In this experimental simulation, we mainly focus on three metrics in the FL-NFT auction process, including

- *The quality of FL-NFT*: the test accuracy of FL-NFT based on MLP-MNIST, MLP-CIFAR-10, CNN-MNIST, and CNN-CIFAR-10. Every independent MU can organize MU-DAO voluntarily for FL-NFT minting.
- *The cost of MU-DAO*: includes the computation cost and privacy cost of MU-DAO recruiting 10 MUs to perform local model training, which can be calculated by Eq.(5).
- *The utility of MU-DAO* : is calculated by the received reward from the MSP bids and the cost of FL-NFT minting. The calculation equation is shown in Eq.(14).

1) The quality of FL-NFT

As described above, in each epoch of PMS-AM, MUs need to adjust the training strategies (i.e., local iterations and privacy budget) with different auction bids to maximize the social welfare of an open Metaverse model marketplace. In fact, none of the existing work has considered the same scenario as our work. Inspired by [27], we

[9] https://metamask.io/
[10] https://ropsten.etherscan.io/
[11] https://github.com/shaoxiongji/federated-learning

employ four common training strategies as the baselines, including centralized learning, random-FL, loss-based and gradient-norm. We make comparisons with four baselines under MLP and CNN with MNIST and CIFAR-10 datasets as shown in Fig. 5. In PMS-AM, MUs can adjust the training strategies to organize MU-DAO voluntarily for FL-NFT minting based on the results of IISG. Centralized learning is the selected benchmark scheme. The other three baselines are state-of-the-art decentralized training strategies [27], including random-FL, loss-based and gradient-norm, respectively.

As shown in Fig. 5, when the total budget $B = 5,000$, the centralized learning scheme achieves the highest test accuracy, as all data are collected by a centralized server for model training. Furthermore, in the decentralized training strategies, PMS-AM achieves the highest test accuracy, in which MUs could make the utmost of the rewards to train the local model and are encouraged to choose a privacy budget with a relatively weak perturbation level on the gradient. Specifically, Fig. 5(a) presents the convergence performance in terms of test accuracy for the MLP model under MNIST dataset $\mathcal{D}_M$ assigned to 10 MUs, in which the FL-NFT aggregates 100 epochs through FedAvg algorithm. We would like to highlight that our proposed PMS-AM scheme significantly outperforms the other three decentralized training strategies. We inspect another model (i.e., CNN) and dataset (i.e., CIFAR-10) in Fig. 5(b), Fig. 5(c), and Fig. 5(d), from which we could observe consistent results as Fig. 5(a).

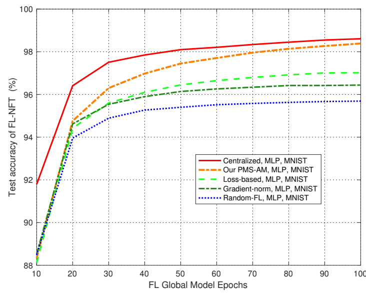
The reason behind it is that the training strategies, including local iterations and privacy budget, can be dynamically adjusted according to the costs and utility of MUs in our PMS-AM. As a result, the MUs are encouraged to allocate resources reasonably to provide more high-quality models. Some fluctuations 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.

2) Cost and Utility of MU-DAO

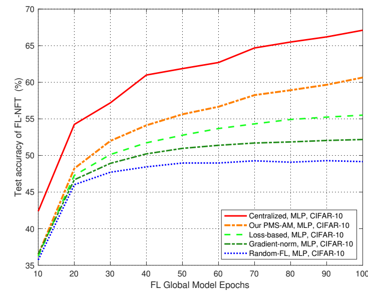
We present the average cost and utility of MU-DAO under four decentralized training strategies in Fig. 6. In this simulation, we assume that the MU-DAO recruits 10 MUs to mint FL-NFT. The configuration of the CPU clock frequency f_i for each MU is randomly generated from the range [3, 5]GHz, and the privacy budget ϵ_i of each MU is randomly generated from the range [1, 5]. We have the following observations. Under four decentralized training strategies, MU-DAO could achieve non-negative utility, validating the IR property. As expected, the highest average utility is achieved in our PMS-AM scheme, as MSPs could change bidding strategies (i.e., different bids for model quality and freshness) under a fixed total budget of $B = 5,000$. In particular, MU-DAO needs higher costs under the CNN model, as in this case, the MUs occupy more computing resources to complete FL-NFT minting. Under the same model, however, MU-DAO with CIFAR-10 dataset consumes higher costs, while random-FL consumes the lowest cost. The reason is mainly the training cost variance among different models, datasets and training strategies.

3) The time of FL-NFT minting

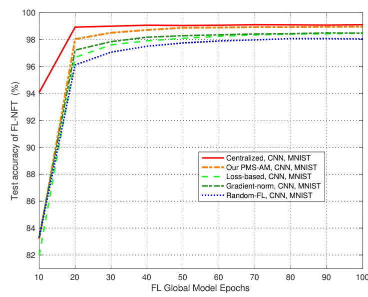
We simulate the process of blockchain-based FL-NFT minting under an Ethereum test network Ropsten. The time of FL-NFT minting includes the FL model training time and blockchain consensus time. The numerical results of the time of FL-NFT minting (i.e., latency) with four different schemes are statistics in table 3. As indicated by the results in table 3, the time of FL-NFT minting with PMS-AM requires more time to complete model training and minting. This is because MUs are incentivized to adjust their training strategies to maximize utility according to the bidding strategies, which increases the time of game decision. The target is to improve the quality of FL-NFT and the utility of stockholders. As the simulation dataset, CIFAR-10 has 60,000 32×32 color images, while MNIST has 60,000 28×28 grayscale images. Due to different sample sizes, FL-NFT minting time is longer under the CIFAR-10 for CNN and MLP models than MNIST. The minting time only represents the comparison trend under different models and datasets, which may vary under different devices. From the current numerical results, we can see that model training and blockchain consensus are both time-consuming tasks, thereby optimizing this scheme from these two aspects need to be explored in the future.



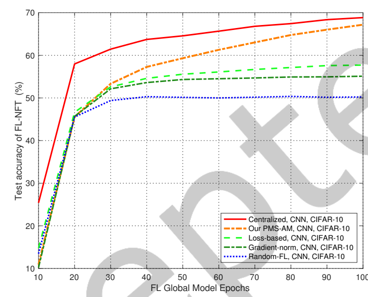
(a) MLP, MNIST



(b) MLP, CIFAR-10

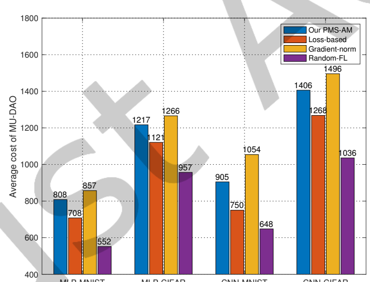


(c) CNN, MNIST

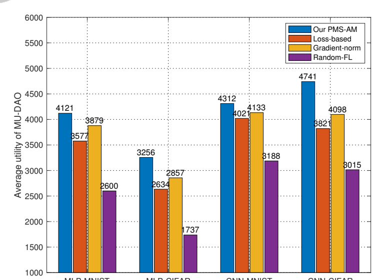


(d) CNN, CIFAR-10

Fig. 5. Comparison of test accuracy of FL-NFT under MLP and CNN with MNIST and CIFAR-10 datasets among the five schemes



(a) The average cost of MU-DAO



(b) The average utility of MU-DAO

Fig. 6. Comparison of the average cost and utility of MU-DAO among four decentralized schemes (Number of MU $N = 10$).

7 CONCLUSION

In this work, we propose an effective FL-NFT minting scheme and privacy-preserving multi-winner sealed-bid auction mechanism (PMS-AM) for FL-NFT in the blockchain-driven Metaverse. Specifically, we establish a decentralized autonomous organization MU-DAO to train the FL global model collaboratively, which can be minted into a novel FL-NFT to control its ownership. The imperfect information Stackelberg game (IISG) is

Table 3. Comparison of the time for FL-NFT minting among four decentralized schemes (s)

Scheme name	MLP-MNIST	MLP-CIFAR10	CNN-MNIST	CNN-CIFAR10
Random-FL	732.82	1361.68	1036.65	8996.30
Loss-base	1651.02	2381.62	1960.53	15086.63
Gradient-norm	1651.44	2336.94	1846.89	14993.67
PMS-AM	2184.85	2863.34	2498.34	16226.34

adopted to model the interactions among MUs and MSPs under the FL cost-benefit framework to maximize their utility, in which the backward induction is adopted to solve the equilibrium solution. We combine the double auction and second price auction to determine the winning bidders and the price of FL-NFT, which can be implemented by blockchain-based auction smart contracts to achieve autonomous execution. Numerical results by simulation present that the quality of FL-NFT can be increased compared with the other three schemes. In the future, we plan to enhance the performance and fairness of the auction mechanism and explore its flexibility and effectiveness in practical application scenarios.

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