Incentive Mechanism Design Toward a Win–Win Situation for Generative Art Trainers and Artists

Haihan Duan, *Member, IEEE*, Abdulmotaleb El Saddik, *Fellow, IEEE*, and Wei Cai, *Senior Member, IEEE*

***Abstract*—The recent development of generative art, a typical category of artificial intelligence-generated content (AIGC), is essentially beneficial for social good, which can help amateurs to create artwork and improve experts' efficiency. However, some artists are opposed to generative art technologies due to the copyright infringement and influence of the artists' way of earning a living, which makes the artists protest against generative art technologies, causing a lose–lose situation. Adversarial attacks against generative model training are potential solutions to address this issue, while the lose–lose situation cannot be improved. To build a win–win situation, a feasible method is to incentivize the artists to actively contribute their artworks to generative model training without influencing their living or infringing copyright, such as data crowdsourcing, but traditional data crowdsourcing methods cannot well fit the generative art area. Therefore, this article builds a blockchain-based trading system for generative model training data collection and generated artwork circulation. Specifically, this article formulates a social welfare maximization problem based on the reverse auction and designs a corresponding incentive mechanism. The conducted theoretical analysis and numerical evaluation demonstrate the effectiveness of the proposed incentive mechanism toward a win–win situation for generative art model trainers and artists.**

***Index Terms*—Blockchain, culture preservation, generative art, incentive mechanism, reverse auction.**

Manuscript received 29 February 2024; revised 29 April 2024 and 29 May 2024; accepted 10 June 2024. Date of publication 4 July 2024; date of current version 3 December 2024. This work was supported in part by the Guangdong Basic and Applied Basic Research Foundation under Grant 2024A1515012323, in part by the Shenzhen Science and Technology Program under Grant JCYJ20210324124205016, in part by The Chinese University of Hong Kong, Shenzhen-White Matrix Joint Metaverse Laboratory, and in part by the Guangdong-Hong Kong-Macao Joint Laboratory for Emotional Intelligence and Pervasive Computing, Artificial Intelligence Research Institute, Shenzhen MSU-BIT University. *(Corresponding author: Wei Cai.)*

Haihan Duan is with Guangdong-Hong Kong-Macao Joint Laboratory for Emotion Intelligence and Pervasive Computing, Artificial Intelligence Research Institute, Shenzhen MSU-BIT University, Longgang, Shenzhen 518172, China, also with the School of Science and Engineering, The Chinese University of Hong Kong, Shenzhen, Longgang, Shenzhen 518172, China and, also with Mohamed bin Zayed University of Artificial Intelligence, Abu Dhabi 50819, United Arab Emirates (e-mail: duanhaihan@smbu.edu.cn).

Abdulmotaleb El Saddik is with Mohamed bin Zayed University of Artificial Intelligence, Abu Dhabi, United Arab Emirates, and also with the Multimedia Communications Research Laboratory (MCRLab), University of Ottawa, Ottawa, ON K1N 6N5, Canada (e-mail: elsaddik@uottawa.ca).

Wei Cai is with the School of Science and Engineering, The Chinese University of Hong Kong, Shenzhen, Longgang, Shenzhen 518172, China (e-mail: caiwei@cuhk.edu.cn).

Digital Object Identifier 10.1109/TCSS.2024.3415631

I. Introduction

In recent years, generative art, a typical category of artificial intelligence-generated content (AIGC), has become a cutting-edge research topic. With the development of model sizes, data amounts, techniques, training skills, and computational resources, generative art has achieved extremely impressive performance in image generation or text-to-image tasks using generative adversarial networks (GANs) [1] (such as BeautyGan [2], StyleGAN [3], and GigaGAN [4]) and diffusion model [5] (such as Stable Diffusion [6], DALLÂ·E 2 [7], and Midjourney[1]).

However, some artists are opposed to generative art for two main reasons [8]: 1) training data involves copyright infringement: the training data of generative art models are crawled from artwork communities without their artists' permission, and the generated images usually show the same artistic style of these artworks; and 2) Gresham's law—"bad money drives out good" [9]: the threshold of artwork creation significantly drops with the appearance of generative art, threatening the artists' way of earning a living. To a certain degree, it will lead to a monopoly that means production belongs to a small proportion of people or companies, which is damaging to humanity and cultural creativity. Therefore, some artists are fighting against generative art, such as the notable protest on *ArtStation*,[2] a famous art platform whose artworks are usually crawled for model training. In this protest,[3] some artists uploaded images of a red prohibition sign with the text "no to AI-generated images" (simplified as "NO AI" tagging), as shown in Fig. 1(a). After that, when the model trainers crawled data with "NO AI" tagging to train their models, the generated images were strongly contaminated by generating terrible results, as shown in Fig. 1(b). Undoubtedly, these protests will cause a *lose–lose situation*, where the artists cannot maintain regular communication and propagation of their artworks in online art communities, while, at the same time, the generative art models are hard to achieve a good performance due to the lack or contamination of data.

To this end, some researchers have utilized adversarial attacks against generative model training [10], where the key idea is to change the original artwork slightly by applying a

[1]https://www.midjourney.com/
[2]https://www.artstation.com/
[3]https://twitter.com/proximasan/status/1603027325188296705?s=20

(a) (b)

Fig. 1. Artists are protesting against generative art. (a) "NO AI" taggings. (b) Generated images.

human-imperceptible perturbation, e.g., Shan et al. [8] applied "style cloaks" to the original artworks to prevent style mimicry. However, the adversarial attacks will definitely be overcome by future countermeasures [8], and the inevitable influence and modification of the original artworks still lead to a *lose–lose situation* for generative model trainers and artists.

In fact, we believe generative art technologies are beneficial for social good, e.g., they can help amateurs create artwork and improve experts' efficiency. Therefore, finding an approach that can balance generative art development and artists' demands is imperative. A feasible method is to incentivize the artists so that they can actively provide their artworks for generative art model training without influencing their living or infringing copyright, similar to data crowdsourcing [11], [12]. However, existing data crowdsourcing methods cannot fit the generative art: 1) art is a subjective discipline, while the existing methods usually apply objective measures for evaluation, e.g., sensing time [13]; and 2) traditional data crowdsourcing methods ignore the derivative value or copyright of the generated artworks by the model based on collected data.

Recently, the development of blockchain has attracted public attention in both academia and industry [14]. Blockchain is a kind of distributed ledger with growing blocks linked by cryptographic hashes first proposed by Chaum [15], which is utilized as the fundamental of cryptocurrencies, such as *Bitcoin* [16] and *Ethereum* [17]. More importantly, the introduction of smart contracts brings the blockchain industry into a new era [18]. Smart contracts are programs that can be automatically executed on a blockchain virtual machine [19], which are transparent, trustworthy, immutable, and can be notarized [14]. Using smart contracts, digital assets (such as images) can be given a public, unique, and noninterchangeable proof of ownership based on nonfungible token (NFT) protocol [20], e.g., ERC-721 Standard. After that, the digital assets can be traded in public markets based on blockchain, such as in *OpenSea* [21].

In this article, we consider applying blockchain to build a system toward a *win–win situation* for generative art model trainers and artists. The blockchain can play an essential role due to the following features: 1) blockchain is the fundamental of cryptocurrency, which naturally supports value exchange [22]; 2) artists can certify their artworks as NFTs to confirm the creators' copyright [23]; and 3) NFTs can be programmed so that the artists can receive a predetermined royalty fee (so-called creator earning in the blockchain industry) each time the NFT exchanges in the market [20]. Therefore, we design a blockchain-driven trading system and propose a corresponding mechanism to achieve social welfare maximization between the generative art model trainers and artists, where the trainers can obtain training data by paying cryptocurrency to the artists, and the artists can earn a sustained profit when the generated artwork NFTs by the generative art models are in circulation.

The contributions of this article are summarized as follows.

1) We present a blockchain-based trading system for training data collection of the generative art model and circulation of artwork NFTs generated by the generative model.
2) We design an incentive mechanism based on the reverse auction and formulate a social welfare maximization problem for both the generative art model trainers and artists. Correspondingly, we propose winner selection and payment determination algorithms to solve the problem.
3) We conduct both theoretical analysis and numerical simulation to demonstrate the effectiveness of the proposed incentive mechanism, which can achieve a win–win situation for the generative art model trainers and artists.

II. Related Work

A. Adversarial Attacks Against Model Training

To protect the artists, a potential way is to disturb the generative art model training. In this case, the most direct approach is to forcibly prevent the model trainers from obtaining available training data, e.g., by applying "NO AI" tagging on art communities such as Fig. 1(a). However, these kinds of approaches are also adverse to the propagation of artworks, which will consequently influence the artists' reputation.

On the other hand, the artists can also apply methods such as adversarial attacks [10]. The adversarial attack was first proposed by Szegedy et al. [24], [25], and "adversarial examples" were introduced to mislead the neural network models using images by applying a certain human-imperceptible perturbation. Currently, there are many studies focusing on adversarial attacks in different areas, such as universal adversarial image perturbations [26], [27], unrecognizable images [28], video recognition [29], and audio and speech [30]. Specific to art, Shan et al. [8] proposed *Glaze*, a tool that allows artists to apply "style cloaks" to their artworks to prevent style mimicry. However, the adversarial attack-based methods have two main shortcomings: 1) with the development of deep neural networks, many studies tried to enhance their robustness to adapt or detect adversarial attacks [31], [32], which means the existing adversarial attacks cannot be regarded as long-term solutions and they will definitely be overcome by future countermeasures [8]; and 2) the adversarial attack-based methods will inevitably influence the original artworks, which still leads to a lose–lose situation for generative model trainers and artists.

Therefore, this article intends to build a win–win situation for generative art model trainers and artists by designing a suitable incentive mechanism rather than roughly preventing the generative art model training using adversarial approaches.

B. Data Crowdsourcing

To achieve a win–win situation, a feasible consideration is to share profits with the data contributors of the generative art model. This intention is similar to data crowdsourcing [11], [12], which can collect data by leveraging the contribution of large groups of individuals. Many studies have discussed data crowdsourcing problems in different research areas, including social networks [33], medical data [34], video surveillance [35], and Internet of Things (IoT) devices [36]. Moreover, there are also some researchers who studied blockchain-based crowdsourcing, e.g., in the areas of mobile computing [13], edge computing [37], energy [38], and federated learning [39]. However, the existing data crowdsourcing methods cannot fully fit the generative art area due to the following reasons: 1) the evaluation metrics in these application scenarios are based on objective measures, e.g., by calculating the sensing time duration [13], but art is a subjective discipline where different people might show completely different feeling to an artwork; and 2) traditional data crowdsourcing methods only focus on the valuation at the moment of data collection, such as a one-shot deal, which means these methods will not consider the derivative value or copyright of the artworks generated by the generative art models that trained by the collected data.

To this end, this article applies blockchain to build a training data collection and generated artwork circulation system, enabling subjective evaluation by the generative art model trainer and automatic profit sharing based on the NFT protocol.

C. Background of NFT Artwork Platforms

Blockchain is a decentralized digital ledger that records transactions across multiple peer-to-peer (P2P) nodes securely and transparently, and an NFT is a protocol of a unique digital asset verified using blockchain, representing ownership or authenticity of items, such as artworks, music, collectibles, game identity, and cultural products [14], [40], [41], [42]. The advent of blockchain technologies has introduced a novel paradigm for artists to store and trade their creations, which is primarily facilitated by the copyright authentication capabilities inherent in NFT protocols, also known as crypto art [43]. Consequently, numerous crypto art platforms and communities have emerged, serving as marketplaces for selling or showcasing artworks. On these platforms, artists often release collections composed of a fixed number of NFTs, each collection embodying a unique art style or thematic elements, either personally crafted or created by generative art models. Among these, *Art Blocks*[4] stands out as a preeminent platform for generative art on Ethereum [17]. Here, artists have the opportunity to display their generative artworks, while collectors can buy pieces using Ethereum. The revenue for artists on this platform includes the initial sale proceeds of the artwork and subsequent royalty fees (termed creator earnings) obtained from future trades of their artworks.

III. System and Problem Formulation

A. System Overview

We design a blockchain-based system illustrated in Fig. 2, where we consider a simplified case where only one generative art model trainer (named requester) wants to request the artists

[4]https://www.artblocks.io/

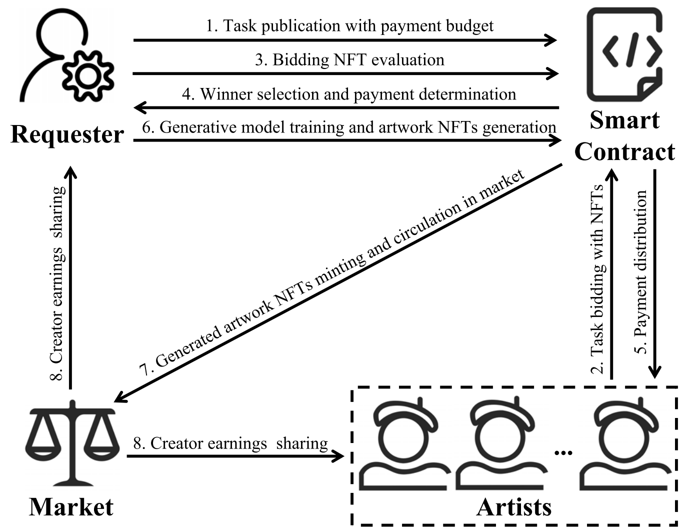


Fig. 2. Framework of the generative art trading system.

to provide artwork to support the generative model training by paying cryptocurrency. The framework consists of eight steps: steps 1 to 5 can collect training data based on a budget-limited reverse auction model [44]; and steps 6 to 8 mainly consider the generative artwork generation and circulation procedure, which will consider the profit sharing of the generated artwork NFTs. The system intends to maximize the social welfare of both the requester and artists by designing a feasible incentive mechanism [45], which can achieve a *win–win* situation for generative art model trainers and artists. The following sections will discuss the details of the social welfare maximization problem. Key notations can refer to Table I.

B. System Formulation

In this section, we first describe the data collection procedure based on a budget-limited reverse auction model [44]. The reverse auction is an auction model in which the traditional roles of buyer and seller are reversed, which consists of a single buyer/requester and multiple sellers [46]. In a reverse auction model, the requester publishes a task, and multiple sellers will bid on the task with their corresponding contributions. Then, the requester can select none or multiple sellers (*winner selection*) and determine the specific payment to each winner according to some strategies (*payment determination*). In our proposed system, the requester is the buyer publishing a data collection task, and the artists are the sellers who provide artworks to participate in the auction. Based on the description, we can formulate the reverse auction model step by step following the framework, as shown in Fig. 2.

1) Task Publication With Payment Budget: In this system, there is a requester $\mathcal{R}$ who wants to collect artworks for generative art model training with a limited budget $\mathcal{B}$. The requester can publish the task requirements with the cryptocurrency budget to the smart contract. Due to the advantage of transparency of blockchain, any platform can crawl the task and advertise it to bulletins of artist communities.

TABLE I
KEY ANNOTATIONS (IN THE ORDER OF APPEARANCE)

Symbol	Definition	Symbol	Definition
$\mathcal{R}$	Requester	$\mathcal{B}$	Budget constraint
$\mathcal{A}$	Artist	n	Total number of artists, $n \in \mathbb{N}$
B, b_i	B: bidding price list; b_i: the ith artwork's bidding price	$\mathbb{C}$, c_i	$\mathbb{C}$: artwork cost list; c_i: the ith artwork's cost
h_i	Selling price of the ith artwork in market, $h_i \geq c_i$	E, e_i	E: evaluation score list; e_i: the ith artwork's evaluation score
$\mathcal{W}$	Winner list	m	Number of winners, $m \in \mathbb{N}$ and $0 \leq m \leq n$
i	Used to denote the ith artwork/artist from all participants	j	Used to denote the jth artwork/artist from the winners
(b_j^*, e_j^*)	jth winner's bidding price and evaluation score	$\mathcal{Q}$	Theoretical quality of the selected dataset (winners)
α, β	Coefficients used to estimate the theoretical dataset quality $\mathcal{Q}$	P, p_j	P: payment list of winners; p_j: the jth winner's payment
U	Generally represents utility; social welfare in function (16)	C	Generally represents cost
$U_{\text{payment}}^{\mathcal{A}_j}$	jth winning artist's utility of payment	$C_{\text{payment}}^{\mathcal{R}}$	Total payment cost that the requester pays to the artists
$C_{\text{training}}^{\mathcal{R}}$	Computational cost of training a deep learning model	d	Batch size the requester presets
T_b	Computational time cost per batch	$\mathcal{E}$	Number of epochs in generative model training
$\mathcal{P}_t$	Unit price of training on graphics processing unit (GPU)	$\mathcal{P}_m$	Offering/initial price for one generative artwork NFT
θ	Creator earning (royalty fee) proportion, $\theta \in [0, 1]$	$\theta^{\mathcal{R}}$	Fixed part of the creator earning for the requester
$\bar{\theta}^{\mathcal{A}}$	Another fixed part of the creator earning for all winning artists	$\theta_{l,j}^{\mathcal{A}}$	jth artist's creator earning proportion of the lth NFT
k	Number of generated artworks by the generative model	$\theta^{\mathcal{A}}$	A $k \times m$ matrix of the artists' creator earning proportion
$U_{\text{selling}}^{\mathcal{R}}$	Income of selling generated artwork NFTs	$v(t)$	NFT collection transaction volume changes over time t
λ, η, τ_1, τ_2	Coefficients used to estimate the collection transaction volume	$\mathcal{V}(\mathcal{Q})$	Total transaction volume changes over dataset quality $\mathcal{Q}$
ω_λ, ω_{τ_1}, ω_{τ_2}	Coefficients used to reflect the relationship of λ, τ_1, τ_2 and $\mathcal{Q}$	$\widehat{\mathcal{V}}(\theta, \mathcal{Q})$	Total transaction volume changes over proportion θ
$U_{\text{creator}}^{\mathcal{R}}$	Requester's utility of creator earnings	$U_{\text{creator}}^{\mathcal{A}_j}$	jth winning artist's utility of creator earnings
$U^{\mathcal{R}}$	Final utility of the requester	$U^{\mathcal{A}_i}$	Final utility of the ith artist

2) Task Bidding With NFTs: After noticing the task, the artists (denoted by $\mathcal{A}$) can bid on it with their possessed artwork NFTs. Without loss of generality, we assume that every artist will participate in the bidding with one NFT to simplify the description, and there are totally $n \in \mathbb{N}$ artists with bidding prices $B = [b_1, b_2, ..., b_n]$. Correspondingly, the cost of drawing the artwork can be represented as $\mathbb{C} = [c_1, c_2, ..., c_n]$. Thus, the winner selection and payment determination algorithms will also treat an NFT as a unit after the bidding. It is worth mentioning that if the ith artwork is not selected as a winner, the artist can sell the artwork for a price $h_i \geq c_i$, because the original purpose of the rational artist is to earn a living by selling the created artwork, which means the rational artists will not sell an artwork for a price less than its cost from a theoretical perspective.

3) Bidding NFT Evaluation: In this step, the requester needs to evaluate every bidding NFT (the artwork from every participated artist) to determine whether it satisfies the task requirements and then assign an evaluation score to each bidding NFT, which is denoted as $E = [e_1, e_2, ..., e_n]$. Facing artworks, this design can support the case that the data requirements of published tasks are abstract and artistic descriptions, e.g., "the quick brown fox jumps over the lazy dog." Nevertheless, in suitable applications, the evaluation process can also be replaced by automatic algorithms, such as image quality assessment methods [47], [48] and object detection methods [49]. For example, the confidence value of object detection methods [49] can be utilized as the evaluation score for some tasks, e.g., a task wants to collect data on dogs, and object detection methods can recognize whether the bidding NFT has dogs. In general, since the bidding NFT evaluation is subjective, the evaluation score (can be regarded as preference) to each bidding NFT is private information of the requester, while the artists do not know before the bidding.

4) Winner Selection and Payment Determination: This step is the core of the reverse auction model. In this article, we will design an incentive mechanism of reverse auction according to Myerson's theorem [50], which satisfies budget feasibility, incentive compatibility, individual rationality, and computational efficiency. The detailed design of the proposed winner selection and payment determination algorithms will be discussed in Section IV. Due to the incentive compatibility, the designed mechanism can guarantee the artists truthfully report the costs as their bidding prices for each artwork, which means the ith bidding NFT has $b_i = c_i$. Then, using the winner selection algorithm discussed in Section IV-B, we can obtain a winner list $\mathcal{W} = [(b_1^*, e_1^*), (b_2^*, e_2^*), ..., (b_m^*, e_m^*)]$, in which a total of $m \in \mathbb{N}$ artists are selected as winners ($0 \leq m \leq n$). The winner list records the order of winners when they are selected into the list, which means the jth winner is selected earlier than the $j+1$th winner. After obtaining the winner list, the theoretical quality $\mathcal{Q}$ of the selected dataset can be estimated from two perspectives: 1) *data size*: the performance of the deep learning model grows logarithmically as training data expands with diminishing marginal utility [51], [52]; and 2) *subjective evaluation*: the collected artworks should better satisfy the requirements of the requester. Therefore, the theoretical quality $\mathcal{Q}$ of the selected dataset can be denoted

$$\mathcal{Q} = \alpha\sqrt{m} + \frac{\beta}{m}\sum_{j=1}^{m} e_j^* \tag{1}$$

where the two terms denote the impact of data size and the average score of subjective evaluation, respectively. In addition, α and β are coefficients, which should satisfy $\alpha \ll \beta$ to denote the number of data that will play a weak role when it meets a sufficient quantity for the generative model training. Similar research settings can refer to studies [52], [53].

5) Payment Distribution: Every selected winner can obtain a certain payment according to the payment determination algorithm in Section IV-C. Let $p_j \geq 0$ denotes the calculated payment of the jth winner so that the payment list can be denoted as $P = [p_1, p_2, ..., p_m]$. Therefore, the jth winning artist can obtain utility of payment $U_{\text{payment}}^{\mathcal{A}_j}$ as

$$U_{\text{payment}}^{\mathcal{A}_j} = p_j. \tag{2}$$

Based on each winning artist's utility of payment, the total payment cost $C_{\text{payment}}^{\mathcal{R}}$ that the requester needs to pay to the artists can be represented as

$$C_{\text{payment}}^{\mathcal{R}} = \sum_{j=1}^{m} p_j. \tag{3}$$

6) Generative Model Training and Artwork NFTs Generation: To generate generative artwork, the requester needs first to train a generative art model using the collected artworks. Based on Justus et al. [54], the computational cost of training a deep learning model can be well estimated as follows:

$$C_{\text{training}}^{\mathcal{R}} = \frac{m}{d} \times T_b \times \mathcal{E} \times \mathcal{P}_t \tag{4}$$

where d is the batch size in model training, so (m/d) denotes the number of batches, T_b is the computational time cost per batch (can be estimated via Justus et al. [54]), $\mathcal{E}$ is the number of epochs, and $\mathcal{P}_t$ is the unit price of training on GPU billed by the computational time cost.

Typically, artwork NFT collections usually publish a fixed number of NFTs [55], e.g., the most notable NFT collection *CryptoPunks*[5] and *Bored Ape Yacht Club*[6] published 10 000 NFTs. This study also considers that the requester will generate k artwork NFTs, omitting the computational cost of the generation since it is significantly lower than the training cost.

After the generation of an artwork collection, the requester can build smart contracts to sell it as NFTs. At this moment, the requester needs to set an initial price $\mathcal{P}_m$ for one generative artwork NFT. Note that $\mathcal{P}_m$ is usually set as a low price to guarantee the NFTs can be sold out since the creator earnings are usually much higher than the selling income [56], [57].

Then, the requester needs to determine the creator earning proportion, which is similar to the proportion of royalty fees to NFT creators each time the NFT is resold in markets [20], [56], [57]. To build a win–win situation, our system also regards the winning artists as the NFT creators who can share the creator earnings, which truly allows the training data providers to share the derivative profit of generated content. The creator earning $\theta \in [0, 1]$ contains a fixed part for the requester $\theta^{\mathcal{R}}$ and another fixed part for all winning artists $\bar{\theta}^{\mathcal{A}}$, where $\theta = \theta^{\mathcal{R}} + \bar{\theta}^{\mathcal{A}}$. Thus, the normal seller (the current owner of the NFT rather than the requester or the artists) of every transaction can obtain $1 - \theta$ of the selling income. Thus, a $k \times m$ matrix $\theta^{\mathcal{A}}$ as the artists' creator earning proportion can be defined as

$$\theta^{\mathcal{A}} = \begin{bmatrix} \theta_{1,1}^{\mathcal{A}} & \theta_{1,2}^{\mathcal{A}} & \cdots \theta_{1,m}^{\mathcal{A}} \\ \theta_{2,1}^{\mathcal{A}} & \theta_{2,2}^{\mathcal{A}} & \cdots \theta_{2,m}^{\mathcal{A}} \\ \vdots & \vdots \ddots & \vdots \\ \theta_{k,1}^{\mathcal{A}} & \theta_{k,2}^{\mathcal{A}} & \cdots \theta_{k,m}^{\mathcal{A}} \end{bmatrix} \tag{5}$$

where $\theta_{l,j}^{\mathcal{A}}$ is the jth artist's creator earning proportion of the lth NFT, and $l, j \in \mathbb{N}, 1 \leq l \leq k, 1 \leq j \leq m$. Thus, $\bar{\theta}^{\mathcal{A}}$ is fixed, meaning the sum of all winning artists' creator earning proportion, and every generated NFT has the same $\bar{\theta}^{\mathcal{A}}$ as

$$\bar{\theta}^{\mathcal{A}} = \sum_{j=1}^{m} \theta_{l,j}^{\mathcal{A}}, \quad \forall 1 \leq j \leq m, j \in \mathbb{N}. \tag{6}$$

Specifically, the creator earning proportion $\theta_{l,j}^{\mathcal{A}}$ can be interpreted as the artist's contribution to each generated artwork NFT. To this end, the precise determination of the creator earning proportion depends on the requester, who can compare the image similarity or correlation between the generated artwork NFT and the artist's bidding NFT (by methods such as structural similarity index [58] and perceptual similarity [59]), or an average proportion. Note that this article mainly considers social welfare maximization, so the creator earning proportion of each artist will not influence the problem formulation.

7) Generated Artwork NFTs Minting and Circulation in Market: Minting NFT refers to the process of offering newly created NFTs to the public through smart contracts [55], which can be regarded as the first transaction of NFTs from their creators to the first trader. At this moment, the requester plays the role of a seller who can obtain the utility of selling income

$$U_{\text{selling}}^{\mathcal{R}} = (1 - \theta) \times k \times \mathcal{P}_m \tag{7}$$

where $1 - \theta$ is the proportion of the seller, k is the number of NFTs, and $\mathcal{P}_m$ is the offering price of one NFT. After NFT minting, the NFTs enter circulation in public markets, where they can be traded among collectors and investors, and the requester and artists can earn profit during the trading.

8) Creator Earnings Sharing: As we mentioned above, the creator earnings will be shared with the artists when each NFT is traded in the markets. Therefore, we can calculate the total creator earnings based on the total transaction volume of the generative artwork NFT collection. In this case, we need to determine the relationship between transaction volume and time, but, to the best of our knowledge, few existing studies can be referred to. To this end, we collect the real transaction data of *Art Blocks* through the crypto data platform *Dune*.[7] As shown in Fig. 3(a), we obtain the data from five famous generative art NFT collections, including *Ringers by Dmitri Cherniak*, *Chromie Squiggle by Snowfro*, *Construction Token by Jeff Davis*, *Genesis by DCA*, and *Singularity by Hideki Tsukamoto*. The data record the weekly change of transaction volume from the NFT minting to 20 February 2023, covering more than two years. However, the vast difference in transaction volume makes Fig. 3(a) difficult to find a pattern, so we normalize the

[5]https://www.larvalabs.com/cryptopunks
[6]https://boredapeyachtclub.com/
[7]https://dune.com/home

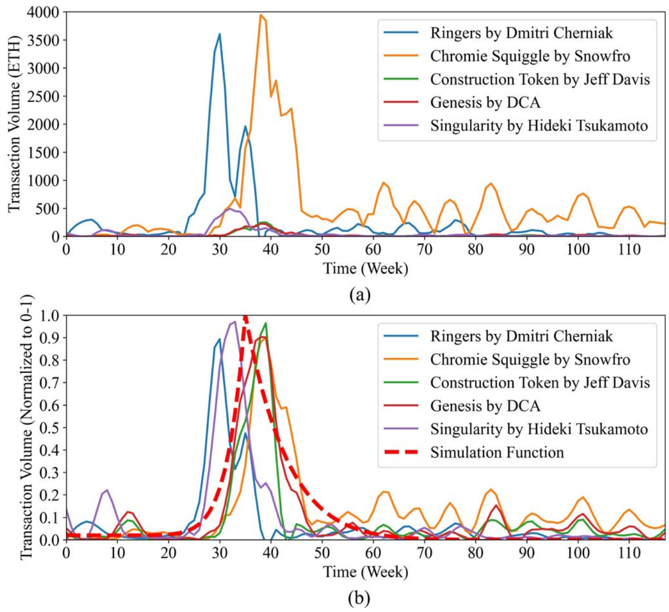


Fig. 3. Five notable generative art NFT collections' transaction volume changes over time. (a) Change of transaction volume over time. (b) Change of transaction volume over time (after normalization).

transaction volume into $[0, 1]$ with a Savitzky–Golay filter [60] to smooth the data trend, as shown in Fig. 3(b). We can find that, no matter which collection, a crucial feature is that the transaction volume may show a sharp increase and decrease in a short period and then keep fluctuations in other periods, which accords the transaction trends [61] due to some reasons such as visual feature [62], NFT hype [63], and cryptocurrency price [43]. To simply reflect the trend feature, we simulate a piecewise exponential function of the transaction volume $v(t)$ as

$$v(t) = \begin{cases} k\mathcal{P}_m + \lambda t^\eta, & 0 \le t < \tau_1 \\ \frac{k\mathcal{P}_m + \lambda\tau_1^\eta}{(\tau_1 - \tau_2)^\eta}(t - \tau_2)^\eta, & \tau_1 \le t \le \tau_2 \end{cases} \tag{8}$$

where $k\mathcal{P}_m$ denotes the volume of NFT minting, $t > 0$ is time, $\lambda > 0$ is a coefficient that decides the maximum volume, $\eta \in \mathbb{N}$ is the exponent that decides the velocity of increase, and the curve will reach the maximum volume at $\tau_1 > 0$ and gradually approach zero at $\tau_2 > 0$. Equation (8) has a flexible parameter setting that can fit different cases. For example, the red dotted curve in Fig. 3(b) illustrates the simulation function, where we set $k \times \mathcal{P}_m = 0.02$, $\eta = 10$, $\tau_1 = 35$, $\tau_2 = 118$, and $\lambda = (1 - 0.02/35^{10})$ to guarantee $v(35) = 1$. Fig. 3(b) shows that the simulation function can well reflect the feature of transaction volume trend. Using the simulation function, the total transaction volume $\mathcal{V}$ can be calculated as

$$\mathcal{V} = \int_0^{\tau_2} v(t)\mathrm{d}t = k\mathcal{P}_m\tau_1 + \frac{\lambda\tau_1^{\eta+1} - (k\mathcal{P}_m + \lambda\tau_1^\eta)(\tau_1 - \tau_2)}{\eta + 1}. \tag{9}$$

As mentioned above, there are many factors that will impact the transaction trend. Since this article mainly focuses on generative art, we only consider the visual feature [62] related to the theoretical quality $\mathcal{Q}$ of the collected dataset [refer to (1)], writing as $\mathcal{V}(\mathcal{Q})$. We assume λ, τ_1, and τ_2 have a positive correlation with quality $\mathcal{Q}$. Considering the marginal value of generative art model performance decreases as the increasing of $\mathcal{Q}$ [53], we use simple concave functions with coefficients $\omega_\lambda > 0$, $\omega_{\tau_1} > 0$, $\omega_{\tau_2} > 0$ to reflect their relationship as a theoretical study, denoted as

$$\lambda = \omega_\lambda\sqrt{\mathcal{Q}}, \quad \tau_1 = \omega_{\tau_1}\sqrt{\mathcal{Q}}, \quad \tau_2 = \omega_{\tau_2}\sqrt{\mathcal{Q}}. \tag{10}$$

On the other hand, the creator earning proportion plays a role of royalty and transaction tax in practice. Tunc et al. [64] indicate that the higher royalty will lead to less NFT market liquid. The transaction tax also presents a similar conclusion, where higher tax will significantly drop the market liquidity demand and supply [65]. However, none of the existing studies can fit a function to present the relationship since no practical application dares to apply very high royalties or tax. Therefore, regarding the feature of "significantly drop," we assume the total transaction volume and creator earning proportion meet an exponential relationship, represented as

$$\widehat{\mathcal{V}}(\theta, \mathcal{Q}) = (1 - \theta)^\gamma \mathcal{V}(\mathcal{Q}) \tag{11}$$

where $\theta \in [0, 1]$, and $\gamma \in \mathbb{N}$ is usually a large integer to reflect the feature of "significantly drop." After calculating the total volume of the generative artwork NFT collection circulation, the requester's utility of creator earnings can be obtained as

$$U^{\mathcal{R}}_{\text{creator}} = \widehat{\mathcal{V}}(\theta, \mathcal{Q}) \times \theta^{\mathcal{R}}. \tag{12}$$

And the jth winning artist's utility of creator earnings is as follows:

$$U^{\mathcal{A}_j}_{\text{creator}} = \widehat{\mathcal{V}}(\theta, \mathcal{Q}) \times \frac{1}{k}\sum_{l=1}^{k} \theta^{\mathcal{A}_{l,j}} \tag{13}$$

where $\theta^{\mathcal{R}}$ is the requester's proportion, and $(1/k)\sum_{l=1}^{k} \theta^{\mathcal{A}_{l,j}}$ is the jth artist's average proportion, recalling k is the amount of generated artwork NFTs by the trained generative model.

C. Social Welfare Maximization Problem

According to the formulations discussed in Section III-B, the final utility of the requester can be estimated as

$$U^{\mathcal{R}} = U^{\mathcal{R}}_{\text{selling}} + U^{\mathcal{R}}_{\text{creator}} - C^{\mathcal{R}}_{\text{payment}} - C^{\mathcal{R}}_{\text{training}} \tag{14}$$

and the final utility of the ith artist $(1 \le i \le n, i \in \mathbb{N})$ is as follows:

$$U^{\mathcal{A}_i} = \begin{cases} p_i + U^{\mathcal{A}_i}_{\text{creator}} - c_i, & \text{if } i\text{th artist is a winner} \\ h_i - c_i, & \text{if } i\text{th artist is not a winner.} \end{cases} \tag{15}$$

The potential selling price h_i of the unselected bidding artwork is private information, but we can reasonably assume $U^{\mathcal{A}_i}_{\text{creator}} + p_i \ge h_i$ and the rational artists' strategies tend to win the auction. Otherwise, the artist will directly sell the artwork for h_i and not participate in the auction. Overall, we can summarize the core problem of this article as follows:

Social Welfare Maximization Problem:

$$\arg\max_{\theta,\mathcal{W}} U = U^{\mathcal{R}} + \sum_{i=1}^{n} U^{\mathcal{A}_i} \quad s.t. \quad \sum_{j=1}^{m} p_j \leq \mathcal{B} \qquad (16)$$

where the objective function (16) is to maximize the social welfare of both the requester and artists, with a constraint of budget limitation. This social welfare maximization problem is a bounded 0–1 integer nonconvex optimization problem, which is a nondeterministic polynomial-time hardness (NP-hardness) problem [66]. Thus, the target of the mechanism design is to find a near-optimal solution in polynomial time.

IV. Incentive Mechanism Design

To near-optimally solve the social welfare maximization problem toward a win–win situation for AIGC model trainers and artists, this section introduces the proposed incentive mechanism Winta, including two algorithms: *winner selection* Winta-WS and *payment determination* Winta-PD. Generally, an effective reverse auction model needs to satisfy the following four properties [13], [53], [67], [68]:

1) *Budget Feasibility*: The total payment of the requester should be less than budget $\mathcal{B}$, as shown in (16).
2) *Incentive Compatibility*: The proposed incentive mechanism should ensure that truthful participants can obtain the maximum utility in the auction, which means setting $b_i = c_i$ is the optimal strategy for the artists.
3) *Individual Rationality*: The auction participants should obtain a nonnegative utility, which denotes $U^{\mathcal{A}_i} \geq 0$.
4) *Computational Efficiency*: The time complexity of the proposed algorithms should be in polynomial time.

The following sections will first discuss the optimal creator earning proportion for the social welfare calculation and then introduce the details of the winner selection algorithm Winta-WS and payment determination algorithm Winta-PD.

A. Optimal Creator Earning Proportion

Before designing the incentive mechanism, the requester needs to find the optimal creator earning proportion θ. Thus, we calculate the first partial derivative of U with respect to θ

$$\frac{\partial U}{\partial \theta} = -k\mathcal{P}_m + (1-\theta)^{\gamma}\mathcal{V}(\mathcal{Q}) - \gamma\theta(1-\theta)^{\gamma-1}\mathcal{V}(\mathcal{Q}). \quad (17)$$

Let $(\partial U/\partial\theta) = 0$, and we have known that $\mathcal{V}(\mathcal{Q}) \gg k\mathcal{P}_m$, thus $(k\mathcal{P}_m/\mathcal{V}(\mathcal{Q})) \approx 0$, so we can obtain two potential near-optimal solutions $\theta \approx 1$ and $\theta \approx (1/\gamma+1)$. Apparently, $\theta \approx 1$ means the whole selling profits will belong to the creator, causing nobody else to be willing to sell the NFTs. On the other hand, we need to prove $\theta \approx (1/\gamma+1)$ is the near-optimal solution.

Lemma 1: For social welfare utility function U, $\theta \approx (1/\gamma+1)$ is the near-optimal creator earning proportion when $\theta \in [0,1]$.

Proof: To prove *Lemma 1*, we need to introduce the theorem of the second-derivative test [69] as follows.

Algorithm 1: Winner Selection: Winta-WS

Input: Budget $\mathcal{B}$, evaluation score $E = [e_1, e_2, ..., e_n]$, bidding price $B = [b_1, b_2, ..., b_n]$, Proportion θ
Output: Winner list $\mathcal{W}$, sorted ratio list Γ'

```
Initialize: Winner list W = [], temp winner list
    W' = [], temp maximum utility U_max = 0, the number
    of auction participants n = |B|, current cost ρ = 0
Γ = [e_1/b_1, e_2/b_2, ..., e_n/b_n];
Γ' = [(b'_1, e'_1), (b'_2, e'_2), ..., (b'_n, e'_n)] (Γ' is a sorted
    version of Γ by setting the higher e_i/b_i at first);
for i = 1 to i = n do
    if ρ + b'_i ≤ B then
        W' = W' ∪ (b'_i, e'_i);
        U' = U(θ, W');
        if U' > U_max then
            W = W', U_max = U', ρ = ρ + b'_i;
        end
        else
            W' = W' \ (b'_i, e'_i);
        end
    end
end
return W, Γ';
```

Theorem 1 (Second-Derivative Test [69]): If a function is twice-differentiable, a local maximum happens when the first derivative at a point is equal to 0 (so-called critical point) and the second derivative at the same point is negative.

The second derivative of U with respect to θ is as follows:

$$\frac{\partial^2 U}{\partial \theta^2} = \mathcal{V}(1-\theta)^{\gamma-2}(\gamma^2\theta + \gamma\theta - 2\gamma). \quad (18)$$

Let $\theta \approx (1/\gamma+1)$, the second derivative of U can be denoted as

$$\frac{\partial^2 U}{\partial \theta^2}\left(\theta \approx \frac{1}{\gamma+1}\right) = \mathcal{V}\left(1 - \frac{1}{\gamma+1}\right)^{\gamma-2} \frac{-\gamma^2-\gamma}{\gamma+1} \quad (19)$$

where $\mathcal{V} \geq 0$ and $\gamma \geq 0$ ($\gamma \in \mathbb{N}$). Thus, the second derivative is $(\partial^2 U/\partial\theta^2) < 0$. According to Theorem 1, the critical point $\theta \approx (1/\gamma+1)$ is the local maximum, which is also the optimal creator earning proportion because there are only two critical points when $\theta \in [0,1]$, and $\theta \approx 1$ is not the solution since this setting will lead to no liquidity in the NFT market. □

In practice, we can find that most NFT collections set $\theta = 5\%$ [70] correspond to $\gamma = 19$, which accords with the very large exponent assumption discussed in (11).

B. Winner Selection Algorithm

As mentioned in Section III-C, the social welfare maximization problem is an NP-hard problem. Therefore, we design an efficient greedy algorithm Winta-WS to select winners (Algorithm 1). The key idea of Winta-WS is to greedily find bidding NFTs with a higher ratio of evaluation score and price under the budget constraint. At first, Winta-WS will obtain a ratio list $\Gamma' = [(b'_1, e'_1), (b'_2, e'_2), ..., (b'_n, e'_n)]$ sorted by the higher ratio of

Algorithm 2: Payment Determination: Winta-PD

Input: Winner list $\mathcal{W} = [(b_1^*, e_1^*), (b_2^*, e_2^*), ..., (b_m^*, e_m^*)]$, budget $\mathcal{B}$, bidding price $B = \{b_1, b_2, ..., b_n\}$, sorted ratio list $\Gamma' = [(b_1', e_1'), (b_2', e_2'), ..., (b_n', e_n')]$, evaluation score $E = [e_1, e_2, ..., e_n]$

Output: Payment list P

1 **Initialize:** *The number of winners* $m = |\mathcal{W}|$*, payment list* $P = [p_1, p_2, ..., p_m]$*, remaining budget* $\mathcal{B}' = \mathcal{B} - \sum_{j=1}^{m} b_j^*$*, temp variable list* $\delta = [\delta_1 = 0, \delta_2 = 0, ..., \delta_m = 0]$
2 $\Gamma^\Delta = \Gamma' \setminus \mathcal{W} = [(b_1^\Delta, e_1^\Delta), (b_2^\Delta, e_2^\Delta), ..., (b_{n-m}^\Delta, e_{n-m}^\Delta)]$;
3 **for** $j = 1$ *to* $j = m$ **do**
4   t = 1;
5   **while** $b_t^\Delta > \mathcal{B}' + b_j^*$ *and* $t \le n - m$ **do**
6   t = t + 1;
7   **end**
8   **if** $t == n - m + 1$ **then**
9         $\delta_j = 0$;
10   **end**
11   **else**
12         $\delta_j = \frac{e_j^* \times b_t^\Delta}{e_t^\Delta} - b_j^*$;
13   **end**
14 **end**
15 **for** $j = 1$ *to* $j = m$ **do**
16     $p_j = \min(b_j^* + \delta_j, b_j^* + \mathcal{B}' \times \frac{\delta_j}{\sum_{t=1}^{m} \delta_t})$;
17 **end**
18 return P;

evaluation score and price (lines 2–3). Then, for every bidding NFT in Γ', Winta-WS will sequentially add each NFT to a temporary winner list $\mathcal{W}'$ if the current cost ρ is less than the budget (lines 4–6). If the estimated utility of social welfare (line 7) is higher than the current temporary maximum utility $U_{\max}$, Winta-WS will update the winner list $\mathcal{W}$, temporary maximum utility $U_{\max}$, and current cost ρ. Otherwise, the temporary winner list $\mathcal{W}'$ will remove the selected NFT (lines 8–13). Finally, Winta-WS will return the winner list $\mathcal{W}$ sorted by the ratio of evaluation score and price and Γ' for the final payment determination (line 16).

C. Payment Determination Algorithm

This section introduces the proposed payment determination algorithm Winta-PD, as shown in Algorithm 2. The key idea of Winta-PD is to determine every winner's payment based on the performance of his/her best candidate. At first, Winta-PD will remove all winners from the list Γ' sorted by the ratio of evaluation score and price to obtain a list Γ^Δ. Nothing that the elements in Γ^Δ have also been in order by higher $(e_t^\Delta / b_t^\Delta)$ first (line 2). For each winner in $\mathcal{W}$, Winta-PD will search his/her best candidate (b_t^Δ, e_t^Δ) with the highest ratio of evaluation score and price under the budget constraint $\mathcal{B}' + b_j^*$, where $\mathcal{B}'$ means the remaining budget after winner selection, so $\mathcal{B}' + b_j^*$ denotes the remaining budget if the jth winner is kicked out from the winner list (lines 3–7). If there is no available candidate, Winta-PD will set a temporary variable $\delta_j = 0$ (lines 8–10). Otherwise, δ_j will be obtained by the following equation $(e_j^*/b_j^* + \delta_j) = (e_t^\Delta / b_t^\Delta)$, thus $\delta_j = (e_j^* \times b_t^\Delta / e_t^\Delta) - b_j^*$, which ensures that the artist will lose the auction when the bidding price is larger than $b_j^* + \delta_j$ (lines 11–14). Strictly, since the artists do not know other participants' bidding prices and evaluation scores before bidding if their bidding prices are higher than costs, they may lose the auction, so the rational participants will tend to be truthful. After the calculation of δ_j, Winta-PD can determine the payment for each winner based on the remaining budget $\mathcal{B}'$. Winta-PD will pay artists according to the proportion of δ_j if the remaining budget $\mathcal{B}'$ is not enough for $b_j^* + \delta_j$ (lines 15–17) to ensure the budget feasibility. Finally, Winta-PD will return the final payment list P (line 18).

V. Evaluation

A. Theoretical Analysis

After introducing the incentive mechanism Winta, this section provides a theoretical analysis to prove that the proposed Winta can satisfy the four properties mentioned in Section IV.

Lemma 2 (Budget Feasibility): The total payment of the requester is less than budget $\mathcal{B}$.

Proof: According to Winta-PD (Algorithm 2), the total cost of the requester for paying the artists can be denoted as

$$C_{\text{payment}}^{\mathcal{R}} = \sum_{j=1}^{m} p_j = \sum_{j=1}^{m} \min\left(b_j^* + \delta_j, b_j^* + \mathcal{B}' \times \frac{\delta_j}{\sum_{t=1}^{m} \delta_t}\right). \tag{20}$$

It is easy to obtain the maximum payment of the requester is as follows:

$$\max(C_{\text{payment}}^{\mathcal{R}}) = \sum_{j=1}^{m} \left(b_j^* + \mathcal{B}' \times \frac{\delta_j}{\sum_{t=1}^{m} \delta_t}\right) = \mathcal{B}. \tag{21}$$

Therefore, the total payment of the requester $C_{\text{payment}}^{\mathcal{R}} \le \mathcal{B}$, which satisfies the budget feasibility. □

Lemma 3 (Incentive Compatibility): The proposed mechanism can ensure that the truthful participants obtain maximum utility.

Proof: To prove Lemma 3, we need to first introduce Myerson's Theorem [50] as follows.

Theorem 2 (Myerson's Theorem [50]): A single-parameter auction mechanism meets the truthfulness if and only if

1) **Monotone Selection:** If a bidder can win the auction by a bidding price b_j, he/she can win the auction by $b_j' < b_j$.
2) **Critical Payment:** The monotone selection implies a critical payment p_j for each participant so that he/she can win the auction by bidding $p_j' \le p_j$; otherwise, he/she will lose.

For any winner (b_j^*, e_j^*), it must meet $(e_j^*/b_j') \ge (e_j^*/b_j^*)$ if $b_j' < b_j^*$. Due to the greedy selection of Winta-WS, the winner can also win the auction by bidding b_j',which satisfies the

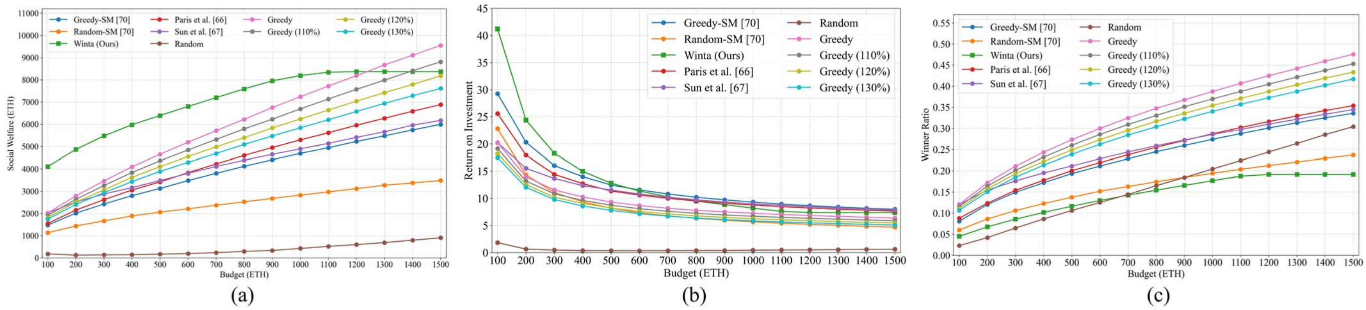


Fig. 4. Trend changes over budget. (a) Social welfare. (b) Return on investment. (c) Winner ratio.

monotone selection. On the other hand, the payment of Winta-PD is associated with the best candidate for each winner. Under this setting, if a winner bids $p'_j > p_j = b^*_j + \delta_j$, he/she will lose the auction and be replaced by the best candidate of the winner because $(e^*_j/b^*_j + \delta_j) = (e^{\Delta}_t/b^{\Delta}_t) > (e^*_j/p'_j)$. Thus, the p_j of Winta-PD is the *critical payment*. Note that the winner will obtain the same payment if $b^*_j \leq b'_j \leq p_j$, but he/she will have a risk of losing the auction if he/she bids $b'_j > b^*_j$, so the rational participants will truthfully submit their bidding prices as the costs because they do not know the critical payment when they are bidding. Overall, according to Theorem 2, the proposed Winta satisfies the incentive compatibility, which can ensure that the truthful auction participants can obtain the maximum utility. □

Lemma 4 (Individual Rationality): The participants of the auction can obtain nonnegative utility.

Proof: According to the final utility $U^{\mathcal{A}_i}$ of the ith artist in (15), if he/she is not selected as a winner, his/her utility is $U^{\mathcal{A}_i} = h_i - c_i$, where $h_i \geq c_i$, thus $U^{\mathcal{A}_i} \geq 0$. If the ith artist is selected as a winner, the utility can be denoted as

$$U^{\mathcal{A}_i} = \min\left(b^*_i + \delta_i, b^*_i + \mathcal{B}' \times \frac{\delta_i}{\sum_{t=1}^{m} \delta_t}\right) + U^{\mathcal{A}_i}_{\text{creator}} - c_i. \tag{22}$$

As Lemma 3 can ensure the reverse auction is truthful ($b^*_i - c_i = 0$), and other terms of $U^{\mathcal{A}_i}$ are greater than 0; thus, it is easy to prove $U^{\mathcal{A}_i} \geq 0$. Therefore, the proposed incentive mechanism Winta satisfies individual rationality. □

Lemma 5 (Computational Efficiency): The time complexity of the proposed algorithms is in polynomial time.

Proof: Since Winta-WS (Algorithm 1) contains the calculation of social welfare (line 7), which needs to be called Winta-PD (Algorithm 2), we first discuss the time complexity of Winta-PD. The time complexity of lines 3–14 in Winta-PD is $O(n(n-m))$, and lines 15–17 is a for loop with $O(m) < O(n(n-m))$, so the time complexity of Winta-PD is $O(n(n-m))$. For Winta-WS, the time complexity of the sorting algorithm (lines 2–3) is $O(n \log n)$, and lines 4–15 are a for loop with nested Winta-PD, which is $O(n^2(n-m)) > O(n \log n)$. Therefore, the time complexity of Winta is $O(n^2(n-m))$, which is in polynomial time and satisfies computational efficiency. □

B. Numerical Simulation

This section conducts a numerical simulation to provide an intuitive performance illustration of the proposed incentive mechanism. The simulation parameters are as follows: coefficients $\alpha = 0.1, \beta = 10$ in (1); batch size $d = 32$, the computational time cost per batch $T_b = 1$, epochs $\mathcal{E} = 100$, the unit price of training $\mathcal{P}_t = 0.01$ in (4); coefficients $\omega_\lambda = 1, \omega_{\tau_1} = 1, \omega_{\tau_2} = 1$ in (10); following with the practical settings in reality, we set the number of the generated artwork NFT collection as $k = 10\,000$, the offering price for one NFT as $\mathcal{P}_m = 0.01$ in (7), and $\theta = 5\%$ (corresponding to $\gamma = 19$) in (11). The numerical simulation will evaluate the trend changing over the budget and the number of participants. We will compare the Winta with existing methods to demonstrate the performance. Since there is no related work that considers the derivative value of collected data, we introduce classic budget feasible mechanisms Greedy-SM and Random-SM [71] as comparison methods, as well as two similar studies [67], [68] of reverse auction after adaptation. The classic greedy algorithm and random selection algorithm are also implemented as comparison methods.

1) Impacts of Budget: To study the impact of budget, we fix the number of participants as $n = 10\,000$ and uniformly generate n participants with bidding price as $p_i \in [0, 1]$ ETH and the corresponding evaluation of each NFT raised by the requester as $e_i \in [0, 1]$. Then, we change budget $\mathcal{B}$ from 100 to 1000 ETH with an increment of 100 ETH. The simulation results are shown in Fig. 4, where (a) shows the trend of social welfare, (b) illustrates the return on investment, and (c) presents the trend of winner ratio changing over the budget.

According to Fig. 4(a), we can find that the social welfare of all methods can increase by increasing the budget. Specifically, the social welfare of Winta can significantly outperform the introduced comparison method [67], [68], [71], particularly when the budget is limited. After the budget reaches 1200, the proposed Winta has a fixed result since the greedy algorithm has searched all bidding artworks, and there is no additional artwork that can increase the estimated social welfare in Algorithm 1. After that, the estimated social welfare of the greedy algorithm exceeds the proposed Winta. However, it is worth noting that the classic greedy algorithm does not have mechanisms to ensure a truthful reverse auction, which means that the participants can increase their bidding price to earn unfair profits, leading to lower performance in practice. Therefore, we also illustrate the untruthful cases that all participants increased by 10%, 20%, and 30% based on their truthful cost during the bidding [Greedy (110%), Greedy (120%), and Greedy (130%) in Fig. 4]. The social welfare shows a significant decrease in the untruthful auction, and the curve of increasing 20% bidding price has been lower than Winta. Nevertheless, the rate of 20% is only a small premium under the auction without any constraints.

From the perspective of return on investment in Fig. 4(b), the performance of all methods drops over the budget increase. The proposed Winta can have a significant performance compared with other methods, but the curve of Winta will cross over that of Greedy-SM [71] when the budget exceeds 600 ETH. The comparison methods of Paris et al. [67] and Sun et al. [68] also perform better than Winta when the budget exceeds 800 ETH, while the gaps are not significant with the increase of the budget. According to the simulated payment data results, we can find that Greedy-SM and Random-SM [71] usually cost only about half of the budget, which leads to a better return on investment when the budget is sufficient, but the social welfare of Winta is approximately 2× and 3× higher than Greedy-SM and Random-SM, respectively. As a result, the experimental results illustrate that Winta can perform better in cases with an extremely limited budget constraint.

The winner ratio in Fig. 4(c) illustrates another typical feature of the proposed Winta, which prefers to select fewer but high-quality participants. Specifically, the winner ratio of Winta becomes the lowest when $\mathcal{B} > 700$ (crossing with the random algorithm), while the experimental results in Fig. 4(a) show that Winta can only use a small proportion of data to achieve higher social welfare. On the contrary, the comparison methods [67], [68], [71] mainly depend on a larger amount of data to improve their performance, whereas the selected participants of Greedy-SM [71], Paris et al. [67], and Sun et al. [68] are approximately 2× more than Winta. Therefore, these results reasonably explain the fore results of social welfare and return on investment, which further enhances the proposed Winta that can well fit the requester who is short of budget.

2) Impacts of the Number of Participants: Then, we focus on the impacts of the number of participants. In this case, we fix the budget as $\mathcal{B} = 500$ ETH with settings similar to the last experiment as $p_i \in [0, 1]$ ETH and $e_i \in [0, 1]$ from the uniform distribution. The number of participants ranges from 8000 to 12 000, with an increment of 1000 participants. As a result, Fig. 5 illustrates the social welfare (a) and the number of winners (b) changing over the number of participants. In addition, we do not present the data of return on investment since the utilized budgets of all methods are almost the same when changing the number of participants according to the experimental results. Therefore, the trend of return on investment is identical to that of social welfare.

As shown in Fig. 5(a), the overall trend of most methods (except the random algorithm) rises when the number of participants increases, which illustrates a near-linear relationship. Specifically, the social welfare of the proposed Winta can be significantly higher than the six comparison methods. Thereinto, the social welfare of Greedy-SM [71], Paris et al. [67], and Sun et al. [68] are close to each other, while Winta achieves

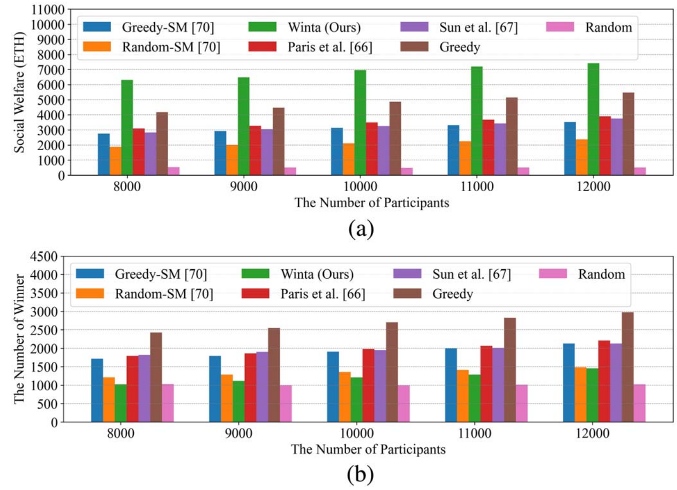


Fig. 5. Data changes over the number of participants. (a) Social welfare. (b) Number of winners.

about 2× more than the three methods. More importantly, Winta can show a higher ratio of margin beyond the greedy algorithm when there are fewer participants. The experimental results demonstrate that Winta is able to select high-quality participants who have higher benefits for social welfare.

The number of winners also shows an increase with the change of participants (except the random algorithm), as shown in Fig. 5(b). Greedy-SM [71], Paris et al. [67], and Sun et al. [68] recruit about 1.5× more participants than Winta, but their social welfare values are only about half of Winta. The greedy algorithm also collects a higher amount of data by containing more participants, about 2× more than Winta, while the social welfare only reaches about (2/3) of Winta. Therefore, the experimental results illustrate that increasing the number of winners cannot directly increase social welfare, and Winta has a better strategy that selects fewer but higher quality winners to achieve good social welfare.

C. Evaluation Summary

Overall, according to the theoretical analysis and numerical evaluation, the proposed Winta can achieve a near-optimal solution to the social welfare maximization problem formulated in Section III-C. The results of the numerical simulation are supplementary illustrations of the theoretical analysis, where Winta outperforms the comparison methods in different budgets and the number of participants. Moreover, the numerical simulation also provides an intuitive perception of the effectiveness and characteristics of the proposed trading system and incentive mechanism. The experimental results demonstrate that Winta can show better superiority by selecting participants with higher quality rather than by increasing the size of the dataset, which brings significant advantages, especially when there are only limited budgets and participants.

VI. Limitations and Future Work

Although the Winta can perform well in the social welfare maximization problem, further efforts could be helpful for addressing the limitations to enhance both the practical and theoretical robustness from the following listed perspectives.

1) While the greedy algorithm-based method provides an efficient and straightforward way of solving reverse auctions, it may prioritize immediate benefits over comprehensive and long-term gains, missing the globally optimal solutions.
2) Since the core problem of this article is to maximize social welfare, in the future, we intend to study the detailed proportion distribution of the creator earnings between the generative art model trainer and each artist, finding the different performances of various distribution methods.
3) The proposed model needs to address some security issues in practice, e.g., the plagiarism of the artworks could be utilized by malicious participants to make a profit. Thus, some decentralized filtering or permission mechanisms of the auction are imperative to safeguard a smooth operation.

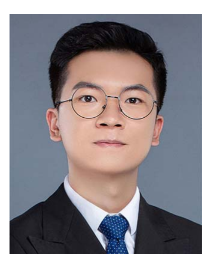
VII. Conclusion

This article proposed a blockchain-based trading system focusing on the social welfare maximization problem of both the generative art model trainers and artists. To solve the problem, this article designed an incentive mechanism based on reverse auction, named Winta, and the theoretical analysis and numerical evaluation proved the feasibility and effectiveness of Winta. Although this work cannot perfectly cover all issues of the proposed idea, we believe this study is a necessary first step toward a *win–win situation* for generative art model trainers and artists. More importantly, a similar consideration can also fit other AIGC areas (such as music, video, and pure text), since these data can be transformed as NFTs on the blockchain platforms to confirm their ownership for the derivative value and profit sharing of the generated content. In summary, we expect our insight to inspire related studies for protecting culture and constructing a more harmonious society.

References

[1] I. Goodfellow et al., "Generative adversarial nets," in *Proc. Adv. Neural Inf. Process. Syst.*, vol. 27, 2014. [Online]. Available: https://papers.nips.cc/paper_files/paper/2014/hash/5ca3e9b122f61f8f06494c97b1afccf3-Abstract.html
[2] T. Li et al., "BeautyGAN: Instance-level facial makeup transfer with deep generative adversarial network," in *Proc. 26th ACM Int. Conf. Multimedia*, 2018, pp. 645–653.
[3] T. Karras, S. Laine, and T. Aila, "A style-based generator architecture for generative adversarial networks," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, 2019, pp. 4401–4410.
[4] M. Kang et al., "Scaling up GANs for text-to-image synthesis," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2023, pp. 10124–10134.
[5] J. Ho, A. Jain, and P. Abbeel, "Denoising diffusion probabilistic models," in *Proc. Adv. Neural Inf. Process. Syst.*, vol. 33, 2020, pp. 6840–6851.
[6] R. Rombach, A. Blattmann, D. Lorenz, P. Esser, and B. Ommer, "High-resolution image synthesis with latent diffusion models," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, 2022, pp. 10684–10695.
[7] A. Ramesh, P. Dhariwal, A. Nichol, C. Chu, and M. Chen, "Hierarchical text-conditional image generation with clip latents," 2022, *arXiv:2204.06125*.
[8] S. Shan, J. Cryan, E. Wenger, H. Zheng, R. Hanocka, and B. Y. Zhao, "Glaze: Protecting artists from style mimicry by text-to-image models," 2023, *arXiv:2302.04222*.
[9] R. Giffen, "The Gresham law," *Econ. J.*, vol. 1, no. 2, pp. 304–306, 1891.
[10] N. Akhtar and A. Mian, "Threat of adversarial attacks on deep learning in computer vision: A survey," *IEEE Access*, vol. 6, pp. 14410–14430, 2018.
[11] H. Garcia-Molina, M. Joglekar, A. Marcus, A. Parameswaran, and V. Verroios, "Challenges in data crowdsourcing," *IEEE Trans. Knowl. Data Eng.*, vol. 28, no. 4, pp. 901–911, Apr. 2016.
[12] F. Daniel, P. Kucherbaev, C. Cappiello, B. Benatallah, and M. Allahbakhsh, "Quality control in crowdsourcing: A survey of quality attributes, assessment techniques, and assurance actions," *ACM Comput. Surveys (CSUR)*, vol. 51, no. 1, pp. 1–40, 2018.
[13] Y. Liu, X. Xu, J. Pan, J. Zhang, and G. Zhao, "A truthful auction mechanism for mobile crowd sensing with budget constraint," *IEEE Access*, vol. 7, pp. 43933–43947, 2019.
[14] W. Cai, Z. Wang, J. B. Ernst, Z. Hong, C. Feng, and V. C. Leung, "Decentralized applications: The blockchain-empowered software system," *IEEE Access*, vol. 6, pp. 53019–53033, 2018.
[15] D. L. Chaum, *Computer Systems Established, Maintained and Trusted by Mutually Suspicious Groups*. Berkeley, CA, USA: Univ. of California Press, 1979.
[16] S. Nakamoto, "Bitcoin: A peer-to-peer electronic cash system," 2008. [Online]. Available: https://assets.pubpub.org/d8wct41f/31611263538139.pdf
[17] V. Buterin et al., "A next-generation smart contract and decentralized application platform," *white paper*, vol. 3, no. 37, pp. 2–1, 2014.
[18] D. Tapscott and A. Tapscott, *Blockchain Revolution: How the Technology Behind Bitcoin Is Changing Money, Business, and the World*. Baltimore, MD, USA: Penguin, 2016.
[19] P. Tolmach, Y. Li, S.-W. Lin, Y. Liu, and Z. Li, "A survey of smart contract formal specification and verification," *ACM Comput. Surveys (CSUR)*, vol. 54, no. 7, pp. 1–38, 2021.
[20] Q. Wang, R. Li, Q. Wang, and S. Chen, "Non-fungible token (NFT): Overview, evaluation, opportunities and challenges," 2021, *arXiv:2105.07447*.
[21] B. White, A. Mahanti, and K. Passi, "Characterizing the OpenSea NFT marketplace," in *Proc. Companion Proc. Web Conf.*, 2022, pp. 488–496.
[22] J. Xu, K. Paruch, S. Cousaert, and Y. Feng, "SoK: Decentralized exchanges (DEX) with automated market maker (AMM) protocols," *ACM Computing Surveys*, vol. 55, no. 11, pp. 1–50, 2023.
[23] L. Kugler, "Non-fungible tokens and the future of art," *Commun. ACM*, vol. 64, no. 9, pp. 19–20, 2021.
[24] C. Szegedy et al., "Intriguing properties of neural networks," 2013, *arXiv:1312.6199*.
[25] I. Rosenberg, A. Shabtai, Y. Elovici, and L. Rokach, "Adversarial machine learning attacks and defense methods in the cyber security domain," *ACM Comput. Surveys (CSUR)*, vol. 54, no. 5, pp. 1–36, 2021.
[26] S.-M. Moosavi-Dezfooli, A. Fawzi, O. Fawzi, and P. Frossard, "Universal adversarial perturbations," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2017, pp. 1765–1773.
[27] M. Duan, K. Li, J. Deng, B. Xiao, and Q. Tian, "A novel multi-sample generation method for adversarial attacks," *ACM Trans. Multimedia Comput., Commun., Appl. (TOMM)*, vol. 18, no. 4, pp. 1–21, 2022.
[28] A. Nguyen, J. Yosinski, and J. Clune, "Deep neural networks are easily fooled: High confidence predictions for unrecognizable images," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2015, pp. 427–436.
[29] L. Jiang, X. Ma, S. Chen, J. Bailey, and Y.-G. Jiang, "Black-box adversarial attacks on video recognition models," in *Proc. 27th ACM Int. Conf. Multimedia*, 2019, pp. 864–872.
[30] Z. Li, Y. Wu, J. Liu, Y. Chen, and B. Yuan, "AdvPulse: Universal, synchronization-free, and targeted audio adversarial attacks via subsecond perturbations," in *Proc. ACM SIGSAC Conf. Comput. Commun. Secur.*, 2020, pp. 1121–1134.
[31] X. Du, C.-M. Pun, and Z. Zhang, "A unified framework for detecting audio adversarial examples," in *Proc. 28th ACM Int. Conf. Multimedia*, 2020, pp. 3986–3994.
[32] J. Yue, H. Li, P. Wei, G. Li, and L. Lin, "Robust real-world image super-resolution against adversarial attacks," in *Proc. 29th ACM Int. Conf. Multimedia*, 2021, pp. 5148–5157.
[33] J. Jiang, B. An, Y. Jiang, C. Zhang, Z. Bu, and J. Cao, "Group-oriented task allocation for crowdsourcing in social networks," *IEEE Trans. Syst., Man, Cybern.: Syst.*, vol. 51, no. 7, pp. 4417–4432, Jul. 2021.
[34] J. Kim and W. Lee, "Stochastic decision making for adaptive crowdsourcing in medical big-data platforms," *IEEE Trans. Syst., Man, Cybern.: Syst.*, vol. 45, no. 11, pp. 1471–1476, Nov. 2015.

[35] P. Korshunov, S. Cai, and T. Ebrahimi, "Crowdsourcing approach for evaluation of privacy filters in video surveillance," in *Proc. ACM Multimedia Workshop Crowdsourcing Multimedia*, 2012, pp. 35–40.
[36] L.-W. Chen and J.-X. Liu, "Mobile crowdsourced guiding and finding with precise target positioning based on Internet-of-Things localization," *IEEE Trans. Syst., Man, Cybern.: Syst.*, vol. 52, no. 8, pp. 4849–4861, Aug. 2022.
[37] L. Fotia, F. Delicato, and G. Fortino, "Trust in edge-based Internet of Things architectures: State of the art and research challenges," *ACM Comput. Surveys*, vol. 55, no. 9, pp. 1–34, 2023.
[38] S. Wang, A. F. Taha, J. Wang, K. Kvaternik, and A. Hahn, "Energy crowdsourcing and peer-to-peer energy trading in blockchain-enabled smart grids," *IEEE Trans. Syst., Man, Cybern.: Syst.*, vol. 49, no. 8, pp. 1612–1623, Aug. 2019.
[39] J. Zhu, J. Cao, D. Saxena, S. Jiang, and H. Ferradi, "Blockchain-empowered federated learning: Challenges, solutions, and future directions," *ACM Comput. Surveys*, vol. 55, no. 11, pp. 1–31, 2023.
[40] S. Pan, G. J. Xu, K. Guo, S. H. Park, and H. Ding, "Video-based engagement estimation of game streamers: An interpretable multimodal neural network approach," *IEEE Trans. Games*, early access, Dec. 2023, doi: 10.1109/TG.2023.3348230.
[41] Y. Djenouri, G. Srivastava, A. Belhadi, and J. C.-W. Lin, "Intelligent blockchain management for distributed knowledge graphs in IoT 5G environments," *Trans. Emerg. Telecommun. Technol.*, vol. 35, no. 4, 2024, Art. no. e4332.
[42] S. Pan, G. J. Xu, K. Guo, S. H. Park, and H. Ding, "Cultural insights in souls-like games: Analyzing player behaviors, perspectives, and emotions across a multicultural context," *IEEE Trans. Games*, early access, Feb. 2024, doi: 10.1109/TG.2024.3366239.
[43] L. Ante, "The non-fungible token (NFT) market and its relationship with Bitcoin and Ethereum," *FinTech*, vol. 1, no. 3, pp. 216–224, 2022.
[44] Y. Singer, "Budget feasible mechanisms," in *Proc. IEEE 51st Annu. Symp. Foundations Comput. Sci.*, Piscataway, NJ, USA: IEEE Press, 2010, pp. 765–774.
[45] Y. Liu, Z. Fang, M. H. Cheung, W. Cai, and J. Huang, "Mechanisms design for blockchain storage sustainability," *IEEE Commun. Mag.*, vol. 61, no. 8, pp. 102–107, Aug. 2023.
[46] J. Zhang, Y. Wu, and R. Pan, "Incentive mechanism for horizontal federated learning based on reputation and reverse auction," in *Proc. Web Conf.*, 2021, pp. 947–956.
[47] Y. Gao, X. Min, Y. Zhu, J. Li, X.-P. Zhang, and G. Zhai, "Image quality assessment: From mean opinion score to opinion score distribution," in *Proc. 30th ACM Int. Conf. Multimedia*, 2022, pp. 997–1005.
[48] L. Seidenari, L. Galteri, P. Bongini, M. Bertini, and A. Del Bimbo, "Language based image quality assessment," in *Proc. ACM Multimedia Asia*, 2021, pp. 1–7.
[49] Z. Zou, K. Chen, Z. Shi, Y. Guo, and J. Ye, "Object detection in 20 years: A survey," *Proc. IEEE*, vol. 111, no. 3, pp. 257–276, Mar. 2023.
[50] R. B. Myerson, "Optimal auction design," *Math. Oper. Res.*, vol. 6, no. 1, pp. 58–73, 1981.
[51] C. Sun, A. Shrivastava, S. Singh, and A. Gupta, "Revisiting unreasonable effectiveness of data in deep learning era," in *Proc. IEEE Int. Conf. Comput. Vis.*, 2017, pp. 843–852.
[52] Y. Zhan, P. Li, Z. Qu, D. Zeng, and S. Guo, "A learning-based incentive mechanism for federated learning," *IEEE Internet Things J.*, vol. 7, no. 7, pp. 6360–6368, Jul. 2020.
[53] S. Fan, H. Zhang, Y. Zeng, and W. Cai, "Hybrid blockchain-based resource trading system for federated learning in edge computing," *IEEE Internet Things J.*, vol. 8, no. 4, pp. 2252–2264, Feb. 2021.
[54] D. Justus, J. Brennan, S. Bonner, and A. S. McGough, "Predicting the computational cost of deep learning models," in *Proc. IEEE Int. Conf. Big Data (Big Data)*, Piscataway, NJ, USA: IEEE Press, 2018, pp. 3873–3882.
[55] N. H. Park et al., "A deep dive into NFT whales: A longitudinal study of the NFT trading ecosystem," 2023, *arXiv:2303.09393*.
[56] M. D. Murray, "NFTs rescue resale royalties? The wonderfully complicated ability of NFT smart contracts to allow resale royalty rights," *J. Law, Technol. Internet*, vol. 14, no. 2, p. 208, 2023.
[57] M. Tunç, T. van den Heuvel, H. Cavusoglu, and Z. E. Zheng, "Impact of resale royalty on primary and secondary sale prices in the non-fungible token marketplace," in *Proc. Conf. Inf. Syst. Technol.*, 2021. [Online]. Available: https://sites.google.com/view/cist2021/
[58] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: From error visibility to structural similarity," *IEEE Trans. Image Process.*, vol. 13, no. 4, pp. 600–612, Apr. 2004.
[59] E. Garces, A. Agarwala, D. Gutierrez, and A. Hertzmann, "A similarity measure for illustration style," *ACM Trans. Graph. (TOG)*, vol. 33, no. 4, pp. 1–9, 2014.
[60] R. W. Schafer, "What is a Savitzky–Golay filter? [Lecture notes]," *IEEE Signal Process. Mag.*, vol. 28, no. 4, pp. 111–117, Jul. 2011.
[61] M. Durban Rodrigues, "Development of a dataframe and a bot to predict NFT-collection performance," B.S. thesis, Univ. Politècnica Catalunya, Barcelona, Spain: UPC Press, 2022.
[62] M. Nadini, L. Alessandretti, F. Di Giacinto, M. Martino, L. M. Aiello, and A. Baronchelli, "Mapping the NFT revolution: Market trends, trade networks, and visual features," *Sci. Rep.*, vol. 11, no. 1, 2021, Art. no. 20902.
[63] C. Pinto-Gutiérrez, S. Gaitán, D. Jaramillo, and S. Velasquez, "The NFT hype: What draws attention to non-fungible tokens?" *Mathematics*, vol. 10, no. 3, p. 335, 2022.
[64] M. M. Tunc, H. Cavusoglu, and E. Zheng, "Resale royalty in NFT marketplaces: Implications for creators and platforms," 2022, *SSRN 4205814*.
[65] P. Gomber, M. Haferkorn, and K. Zimmermann, "Securities transaction tax and market quality—The case of France," *Eur. Financial Manage.*, vol. 22, no. 2, pp. 313–337, 2016.
[66] A. Fréville, "The multidimensional 0–1 knapsack problem: An overview," *Eur. J. Oper. Res.*, vol. 155, no. 1, pp. 1–21, 2004.
[67] S. Paris, F. Martignon, I. Filippini, and L. Chen, "An efficient auction-based mechanism for mobile data offloading," *IEEE Trans. Mobile Comput.*, vol. 14, no. 8, pp. 1573–1586, Aug. 2015.
[68] P. Sun, X. Chen, G. Liao, and J. Huang, "A profit-maximizing model marketplace with differentially private federated learning," in *Proc. - IEEE Conf. Comput. Commun. (INFOCOM)*, Piscataway, NJ, USA: IEEE Press, 2022, pp. 1439–1448.
[69] A. C. Chiang, *Fundamental Methods of Mathematical Economics*. New York, NY, USA: McGraw Hill, 1984.
[70] L. van Haaften-Schick and A. Whitaker, "From the artist's contract to the blockchain ledger: New forms of artists' funding using equity and resale royalties," *J. Cultural Econ.*, vol. 46, no. 2, pp. 287–315, 2022.
[71] N. Chen, N. Gravin, and P. Lu, "On the approximability of budget feasible mechanisms," in *Proc. 22nd Annu. ACM-SIAM Symp. Discrete Algorithms*, Philadelphia, PA, USA: SIAM, 2011, pp. 685–699.



Haihan Duan (Member, IEEE) received the B.Eng. degree in computer science and technology from the East China Normal University, Shanghai, China, in 2017, the M.Eng. degree in software engineering from Sichuan University, Chengdu, China, in 2020, and the Ph.D. degree in computer and information engineering from The Chinese University of Hong Kong, Shenzhen, China, in 2023.

He is currently an Associate Professor with Guangdong-Hong Kong-Macao Joint Laboratory for Emotion Intelligence and Pervasive Computing, Artificial Intelligence Research Institute, Shenzhen MSU-BIT University (SMBU), Shenzhen, China. Before joining SMBU, he worked as a Postdoctoral Research Fellow with the University of Ottawa, Ottawa, ON, Canada, and Mohamed bin Zayed University of Artificial Intelligence (MBZUAI), Abu Dhabi, United Arab Emirates. His research interests include multimedia, blockchain and Web3, metaverse, human-centered computing, and medical image analysis.

Abdulmotaleb El Saddik (Fellow, IEEE) received the Dipl.-Ing. degree in electrical and computer engineering from Darmstadt University of Technology, Darmstadt, Germany, in 1995, and the Dipl.-Ing. degree in electrical and computer engineering from Darmstadt University of Technology, in 2001.

He is the Acting Chair of the Computer Vision Department, MBZUAI, Abu Dhabi, United Arab Emirates, and a Distinguished University Member of the University of Ottawa, Ottawa, ON, Canada. He is an internationally recognized scholar who has made strong contributions to the knowledge and understanding of intelligent multimedia computing, communications, and applications. He has coauthored 10 books and more than 600 publications, chaired more than 50 conferences and workshops, and supervised more than 150 researchers. His research focus is on the establishment of digital twins to enhance the quality of life of citizens using AI, the IoT, SN, AR/VR, haptics, and 5G to allow people to interact in

real time with one another as well as with their smart digital representations in the metaverse.

Dr. El Saddik is a fellow of the Royal Society of Canada (FRSC), the Institute of Electrical and Electronics Engineers (FIEEE), the Canadian Academy of Engineering (FCAE), and the Engineering Institute of Canada (FEIC). He is an ACM Distinguished Scientist and has received several awards, including the Friedrich Wilhelm Bessel Award from the German Humboldt Foundation and the IEEE Instrumentation and Measurement Society Technical Achievement Award. He also received the IEEE Canada C. C. Gotlieb (Computer) Medal and the A. G. L. McNaughton Gold Medal for important contributions to the field of computer engineering and science, and the IEEE TCSC Achievement Award for Excellence in scalable computing. He is the Editor-in-Chief of *ACM Transactions on Multimedia Computing, Communications and Applications (ACM TOMM)*.

Wei Cai (Senior Member, IEEE) received the B.Eng. degree in software engineering from Xiamen University, Xiamen, China, in 2008, the M.S. degree in electrical engineering and computer science from Seoul National University, Seoul, Korea, in 2011, and the Ph.D. degree in electrical and computer engineering from The University of British Columbia (UBC), Vancouver, BC, Canada, in 2016.

He was a Postdoctoral Research Fellow, from 2016 to 2018. He is currently an Assistant Professor in computer engineering with the School of Science and Engineering, The Chinese University of Hong Kong, Shenzhen, China. He is serving as the Director of the Human-Crypto Society Laboratory, Shenzhen, China, and the Director of the CUHK(SZ)-White Matrix Joint Metaverse Laboratory, Shenzhen, China. He has co-authored more than 100 journal and conference papers in the areas of distributed/decentralized systems and interactive multimedia.

Dr. Cai is an Associate Editor of IEEE TRANSACTIONS ON COMPUTATIONAL SOCIAL SYSTEMS, IEEE TRANSACTIONS ON CLOUD COMPUTING, and *ACM Transactions on Multimedia Computing, Communications and Applications*, and a Program Co-Chair for ACM NOSSDAV'23. He was a recipient of six best paper awards. He is a member of the ACM.