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Pricing Mechanism of Non-fungible Token (NFT) Driven by Rarity Design

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***Abstract*—The non-fungible tokens (NFTs) are unique cryptocurrencies that exist on a blockchain and cannot be replicated. However, today's NFT market lacks a sensible pricing framework, which causes NFT price fluctuations to interfere with the investment market. The purpose of this research is to build the pricing mechanism for NFT, as it is directly related to the detailed traits of NFT. The rarity design serves as the driving force behind the proposed pricing mechanism. We present a prototype pricing and minting algorithm and implement it through a smart contract to assess both pricing accuracy and transaction performance. Our proposed mechanism employs specific parameters and data points related to NFT features, which could encompass floating-point values due to our integration of Ether within the regression formula. The experimental results showed that the rarity score of the features has a certain degree of impact on the NFT price.**

***Index Terms*—Blockchain, Non-fungible Token, Pricing, Smart Contract.**

1. Introduction

Non-fungible Tokens, often referred to as NFTs, are tokens based on blockchain, which have proven to be used in various realms, such as traffic management [1] and the combination with machine learning [2]. NFTs are unique and irreplaceable virtual assets that have garnered substantial attention in recent years, peaking in 2021 [3]. This research focuses on NFT pricing, exploring its significance in economics, markets, and regulations. Several crucial aspects need consideration in NFT pricing research.

Economics, influenced by supply and demand, is a primary pricing factor. Variables like the number of participants, market competition, and potential transaction revenue contribute to pricing. Artistry is also pivotal, given NFTs' uniqueness, akin to artwork. Their valuation affects the art industry, considering digital art market attributes, demand, regulations, pricing methods, and trends.

Metadata analysis is vital since NFT pricing depends on data like artist identity, creation date, work details, copyright info, and traits in this paper. It aids in assessing NFT value and the impact of these factors on pricing trends. Another aspect is blockchain tech, which underpins NFT creation, execution, and value transfer via specialized smart contracts. Developers often use metadata and value mechanisms for contract design, demanding clear rules for transaction values. This convergence of finance and blockchain enhances Fintech.

The legal aspect in NFT research is crucial due to its susceptibility to illegal activities like money laundering, further amplified by price volatility. Compared to traditional art, NFTs have unique qualities that attract money launderers: They offer inherent anonymity as cryptographic assets, making regulatory oversight challenging. Being digital assets, NFTs trade online with high liquidity and minimal expenses, contributing to their appeal. The absence of standardized pricing mechanisms allows price manipulation, like wash trading. Existing regulatory frameworks have gaps that can be exploited. Additionally, the straightforward NFT minting process facilitates money laundering.

Although there are some researches that examine the factors that influence the price of NFT [4], [5], [6], [7], few research combines detailed rarity and smart contract. In this research, we further explore how rarity factors impact NFT pricing. Although different collections of NFTs may have different features for the different smart contracts they are based on, there might be a similar method to build a function to express their prices.

Focusing on the characteristics of each NFT, the main goal of this study is to develop an NFT pricing model that enhances liquidity for these assets in Decentralized Finance (DeFi). Our research focuses on capturing the unique value of each NFT. In summary, this study contributes to:

- We propose a NFT pricing model driven by hedonic regression. Unlike other studies, our hedonic regression model is based on the rarity data of NFT traits.
- We design a smart contract that aligns with our proposed pricing model, encompassing the algorithm designed to streamline the NFT pricing calculation and minting into a unified process.
- In the experiments, we first construct and evaluate the pricing model for real-world NFT datasets. Then, we implement the smart contract and measure the transaction performance.

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2. Related Work

In the realm of NFTs, researchers have explored various perspectives, examining market-side, financial, and sell-side factors that collectively shape the NFT landscape. Market-side factors delve into the unique culture of NFT communities, where consensus on specific NFT collections sparks discussions in online forums. Twitter, as a widespread international platform, is used by NFT project owners to promote their offerings, potentially influencing NFT valuation. Kapoor [8], for instance, employed scatter plots and machine learning algorithms to establish correlations between Twitter followers and NFT asset values, akin to Luo's [9] research.

Analysis of financial factors reveals that NFTs, as a nascent investment instrument, are vulnerable to volatility from both traditional financial markets and Web3-related factors. Investigating the relationships between traditional financial variables and NFT metrics, such as returns [10], sales volume [11], and NFT attention [12], provides valuable insights into NFT pricing dynamics. Christopher [4] also established a connection between NFT value and the metaverse using the hedonic model.

On the sell side, factors encompass NFT characteristics and inter-NFT influences. Rarity assumes a pivotal role, with scarcer NFTs commanding elevated prices and experiencing lower transaction frequencies [5], [13]. An intriguing aspect pertains to the impact of racial colour, wherein figures with lighter hues tend to command higher prices [6]. Furthermore, certain studies [14] spotlight the cointegration of NFT submarkets, elucidating how the success of newer projects reverberates across established markets and vice versa.

In addition to non-technical factors, the design of the smart contract significantly influences NFT pricing. Initially, NFTs follow the ERC-721 standard [15] for their creation, forming the basis for Ethereum's NFT market. Developers typically assign an initial NFT price, which can be randomly selected and may change over time due to market dynamics. As the NFT market evolves, various ERC standards, such as ERC-2981 [16], address multi-token transactions, copyright issues, and automated NFT pricing by incorporating royalties based on the original price.

Within the framework of ERC standards, Ethereum encourages innovative smart contract and NFT designs, resulting in diverse contract variations. For example, cross-chain auction protocols offer alternative transactional solutions [17]. However, these variations don't definitively establish a consistent NFT valuation, potentially leading to discrepancies among similar NFTs.

The concept of hedonic regression, proposed by Sherwin Rosen in "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition" [18], suggests product value is a composite of attributes. The hedonic model has been applied in NFT research [4], [7], [13], [19]. Some NFT studies employing hedonic models consider meta-universe factors [4], specific NFT collections [13], or quantity related to NFT characteristics [7]. However, few delve into detailed characteristics of specific NFT collections and their relationship with pricing models.

Machine learning relies on statistical models for computer systems to learn patterns. Researchers aim to uncover the statistical mechanisms of NFT using machine learning algorithms [20], [21], [22], [23].

3. Proposed Pricing Mechanism

This section introduces a novel NFT pricing framework. It utilizes factor analysis to synthesize multiple variables into composite indicators. We present a rarity-driven model. To implement this model on the blockchain, we propose the design of a smart contract to address potential issues.

3.1. Explore Multidimensional Factors

In practical research, data collection is crucial for understanding objectives, but it can lead to overlap and excessive computation. Removing variables may result in data loss. Factor analysis synthesizes variables into composite indicators (factors), reducing dimensionality while minimizing data loss.

We assume a random vector $Y = (y_1,..., y_p)'$ with an average of μ, where $l_{p,m}$ represents the loading. $y_p - \mu_p$ centralizes the data, which SPSS handles automatically in our experiments. When factors are uncorrelated, factor loadings are the correlation coefficients between the pth feature rarity and the mth factor. Higher absolute factor loadings indicate stronger correlations. This model assumes that feature rarity Y depends linearly on m unobservable common factors $F = (f_1,...,f_m)'$ and p unobservable special factors $\varepsilon = (\varepsilon_1,...,\varepsilon_p)'$. The orthogonal factor model is expressed as:

$$\begin{aligned} y_1 - \mu_1 &= l_{1,1}f_1 + l_{1,2}f_2 + ... + l_{1,m}f_m + \varepsilon_1 \\ y_2 - \mu_2 &= l_{2,1}f_1 + l_{2,2}f_2 + ... + l_{2,m}f_m + \varepsilon_2 \\ &... \\ y_p - \mu_p &= l_{p,1}f_1 + l_{p,2}f_2 + ... + l_{p,m}f_m + \varepsilon_p \end{aligned} \quad (1)$$

In the formula above, coefficient $l_{j,k}$ refers to the loading of the ith feature rarity on the kth factor, expressing the characterization of this factor on this feature rarity. If we use matrix signal, the formula above can be rewritten as below, in which $L_{p\times m}$ is the loading matrix:

$$Y_{p\times 1} - \mu_{p\times 1} = L_{p\times m} \times F_{m\times 1} + \varepsilon_{p\times 1} \quad (2)$$

In our research, one key concept is and factors' variance contribution. It refers to the sum of the square of elements of the mth column in the factor loading matrix, reflecting the ability of the mth factor to explain the total variance of the original variable. The higher this figure is, the more important the factor is.

$$S_m^2 = \sum_{p=1}^{w} a_{m,p}^2 \quad (3)$$

In a nutshell, the orthogonal factor model is the core of factor analysis. It can be expressed in two ways. The first one is a matrix-like model:

$$Y - \mu = LF + \varepsilon \quad (4)$$

3.2. Rarity-Driven Model for NFT Pricing

In the preceding section, we elucidated the application of factor analysis as a sophisticated technique for the amalgamation of diverse variables. In this section, we shall commence by examining the conventional iteration of the hedonic model in NFT pricing. Subsequently, we will undertake the intricate task of model reconstruction through the lens of factor analysis.

The hedonic model is used to estimate the impact that external factors and internal characteristics have on the prices of assets and properties [24]. Compared to other research based on the hedonic model, our hedonic model focuses on NFT features. In our research, the implementation of the above concept can be expressed as the formula below:

$$P_i = a + \sum_{j=1}^{J} \alpha_j x_{j,i} + e_i \tag{5}$$

where P_i represents the sale price of an NFT, a is the regression intercept, $\sum_{j=1}^{J} \alpha_j x_{j,i}$ denotes the traits that single NFT has. $x_{j,i}$ refers to variable j of the ith NFT has. The coefficient α_j reflects the attribution of a relative shadow price to each of the j characteristics. e_i is the difference between the predictive value and the real value. Equation 8 is the formula of the hedonic model with common factors.

$$P_i{}' = b + \sum_{j=1}^{J} \beta_j y_{j,i} + u_i \tag{6}$$

where $P_i{}'$ represents the sale price of an NFT, b is the regression intercept. $y_{j,i}$ refers to common factor j of the ith NFT has. The coefficient β_j reflects the attribution of a relative shadow price to each of the j characteristics. u_i is the difference between the predictive value and real value.

When considering factor analysis, the construction of the model has a slight alteration. Figure 1 shows Before and after using factor analysis on hedonic model. Table 1 shows two NFT collections' features. The rarity of these features will be selected for the following model fitting.

TABLE 1. FEATURES OF HV-MTL AND SAPPY SEAL

HV-MTL	Sappy Seal
Back Attachment	Background
Body	Body
Companion	Extra
Crest	Face
Faceplate	Head
Head	Skin
HV Type	N/A
Weapon System	N/A

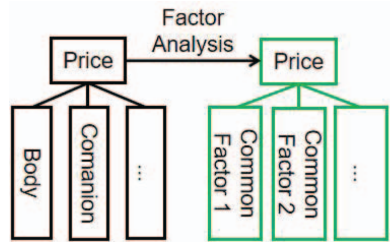

Figure 1. Before and after using factor analysis on hedonic model

3.3. Smart Contract Design

To implement the pricing model in an Ethereum smart contract, adherence to ERC standards is crucial for NFT issuance. Additionally, we present Algorithm 1, which seamlessly combines NFT pricing and minting processes. This algorithm takes a token ID and NFT feature data as input and calculates the NFT's price using a predefined formula. If the price is negative, an error is returned, as negative prices are not allowed. The calculated price and feature data are stored in an NFTData structure, associating the token ID with the NFT's price and features for future reference. The algorithm also supports NFT minting, allowing the contract owner to mint a new NFT using the provided token ID and feature data, typically assigning it to the contract owner. This comprehensive algorithm streamlines NFT pricing calculation and minting, ensuring accurate pricing and proper NFT ownership allocation.

In addition to the algorithm mentioned, establishing a standardized price unit is essential due to Solidity's integer operation constraint. Our proposed model involves parameters and NFT data that may include floating-point numbers, as Ether is used in the regression formula. To enhance pricing precision, we introduce an encompassing price unit in our smart contract: GWei (Giga-Wei), with a conversion rate of 1 Eth $= 1 \times 10^9$ GWei. Within the contract, the transactional price unit is in Wei, and when minting NFTs, GWei is converted to Wei using the relationship 1 GWei $=$ 1×10^9 Wei. Parameters and data points in the formula are appropriately scaled for accuracy. However, it's important to note that actual transactions will require JavaScript scripts to convert GWei to Ether prices, which falls outside the current research scope. This approach, combined with our NFT Pricing and Minting algorithm, strengthens our pricing mechanism's effectiveness and ensures compatibility with Solidity's constraints.

4. Experiments and Evaluation

In this section, we will conduct experiments and analyses to build and assess our pricing model. We will begin by selecting NFT datasets, and processing and analyzing them to determine precise model parameters for a specific NFT category. Next, we will evaluate the model's performance through contract implementation and a comparative study.

Algorithm 1: NFT Pricing and Minting

Input : Token ID $tokenId$ and NFT features $V_1, V_2, V_3, \ldots, V_j$

Output: Calculated NFT price and NFT array with feature values

$Price \leftarrow a + \sum_{j=1}^{J} \beta_j V_j + e$;

if $Price < 0$ **then**

  return *Error: Price cannot be negative*

end

$nftData[tokenId] \leftarrow NFTData(Price, V_1, V_2, V_3, \ldots, V_j)$;

return $mint(msg.sender, tokenId)$;

The outcomes of these evaluations will inform our subsequent discussions and assessments.

4.1. Data Collection

We collected the data described in this section. The NFT data is derived from OpenSea, one of the greatest NFT online markets. The data of 1808 NFTs is from Sappy Seals and 2153 NFTs is from HV-MTL. Trait rarity data on each NFT is calculated as:

$$rarity = \frac{N_f}{N_t} \tag{7}$$

where N_f refers to the number of NFTs having this feature, and N_t refers to the total number of NFTs in the collection. For the convenience of data analysis, we multiply each rarity rate by 100. Before using the hedonic model, we will first do a linear correlation analysis to get early testing of the suitability of linear regression for the datasets. In order to make it more direct, correlation is absolutized:

$$C_1 = abs(C_0) \tag{8}$$

where C_1 is the absolutized correlation and C_0 is the original correlation. In Figure 2 and Figure 3, color legends from left to right indicate an increasing correlation. From these two graphs, it can be seen that there is some correlation between the features of HV-MTL, while the correlation between the features of Sappy Seal is not as strong. Therefore, the hedonic model, as one of the linear regression models, is predicted to perform better in HV-MTL.

4.2. Experimental Results

Factor analysis can combine original variables into shared factors. In our upcoming experiments, we will explore its potential to improve our model's outcomes. This investigation aims to assess factor analysis's impact on our model's performance.

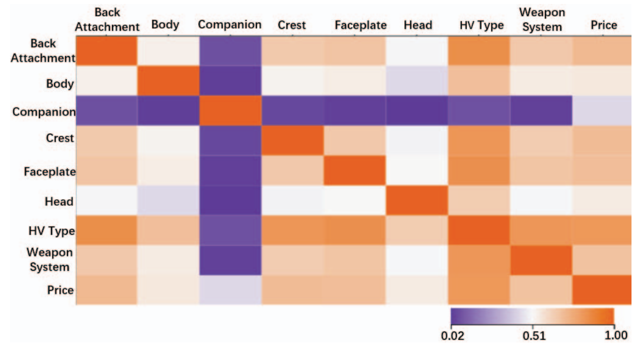

Figure 2. Heatmap of feature correlations in the HV-MTL dataset.

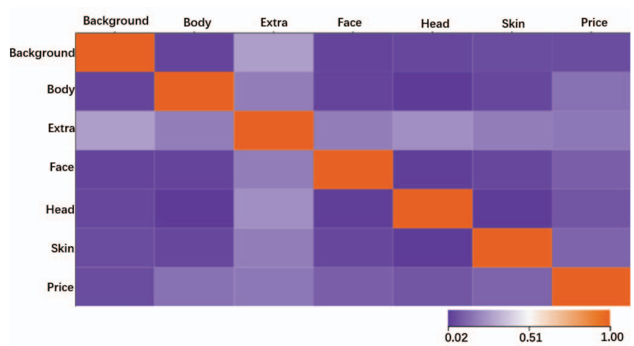

Figure 3. Heatmap of feature correlations in the Sappy Seal dataset.

4.2.1. Data Pre-processing.

Since different indicators have different quantitative outlines and may not be comparable, it is necessary to standardize the raw data to eliminate the effect of quantitative outlines. The standardization formula is as follows, in which X_i is the original data and Z_i is the standardized data:

$$Z_i = X_i - \mu \tag{9}$$

4.2.2. Adaptive Analysis.

Before factor analysis, it's essential to ensure enough correlation among the original variables, a prerequisite for the analysis. Bartlett's and Kaiser-Meyer-Olkin (KMO) tests assess this. If the p-value is less than a, the original variables are suitable for factor analysis.

The KMO test, ranging from 0 to 1, measures variable correlation. Values closer to 1 indicate a stronger correlation, making data more suitable for factor analysis. When KMO ¿ 0.6 and Bartlett's test is significant [25], data is fit for factor analysis. Table 2 confirms both datasets' suitability.

TABLE 2. ADAPTIVE ANALYSIS OF TWO DATASETS

	HV-MTL	Sappy Seal
KMO	0.731	0.635
Significant	0.000	0.000

4.2.3. Number of Common Factors. In order to determine the number of common factors, it is important to observe the result of the total variance. The calculation of the total variance is below:

- Assume S_1^2, S_2^2, ..., S_p^2 are p common factor variance;
- The first variance is C_1 = S_1^2 / p
- The accumulative variance contribution of the first k common factors are C_k = $\sum_{i=1}^{k} S_i^2$ / p

The higher the accumulative variance is, the better common factors can explain the original variables. Generally, 85% is a critical value. As such, according to Figure 4, we can select four common factors in both datasets.

4.2.4. Regression Result. This study aims to evaluate the proposed pricing model within a smart contract. We require data from previous datasets to derive a regression formula. After reviewing Table 3 and analyzing regression results, the HV-MTL result is chosen as the ideal candidate. The formula is as follows:

$$\begin{aligned} p =& 3.638 + 0.206x_1 - 1.202x_2 - 0.007x_3 \\ & - 0.322x_4 + 0.208x_5 - 2.035x_6 \\ & - 0.116x_7 + 0.143x_8 \quad (p > 0) \end{aligned} \tag{10}$$

4.3. Comparison Analysis

We employ the hedonic model to predict NFT prices, with a focus on rarity. Table 4 shows the performance of the hedonic model. The data in Table 4 indicates that the hedonic model can explain over 25% of the HV-MTL dataset variation. Notably, after incorporating common factors, the model demonstrates improvements compared to its initial state. This improvement is evident in the increase of the R^2 value from 0.251 to 0.27, and a decrease in the Mean Absolute Error (MAE) from 0.535 to 0.518.

We also applied the Sappy Seal dataset to our experiment. Table 4 indicates that the introduction of common factors has a slightly negative impact on the results in this case. It worsens the model fit across all indices. Therefore, the performance differences between the HV-MTL and Sappy Seal datasets suggest that the application of factor analysis is likely to yield positive effects on the model when there is a high correlation between variables. However, caution is needed when considering its implementation in cases where such a high correlation is absent.

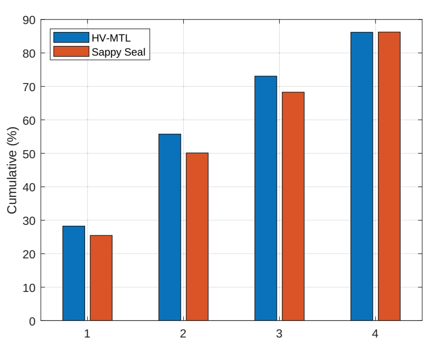

Figure 4. The total variance of growing components in the HV-MTL and Sappy Seal datasets.

TABLE 3. REGRESSION RESULT OF HV-MTL AND SAPPY SEAL

	Dependent Variable of HV-MTL	**Dependent Variable of Sappy Seal**
Constant	3.638	2.032
Feature 1	0.206	0.015
Feature 2	-1.202	-0.01
Feature 3	-0.007	-0.015
Feature 4	-0.322	-0.001
Feature 5	0.208	-0.01
Feature 6	-2.035	-0.005
Feature 7	-0.116	N/A
Feature 8	0.143	N/A

4.4. Contract Implementation and Cost Analysis

Based on the contract design and Formula (12) from the selected dataset, we specify parameter values to ensure contract integrity. To address the issue of excessive NFT feature storage, we introduce an internal price computation function. This function reduces the proliferation of local variables and effectively manages over-stacking by returning the calculated price to the original calculation function.

The modified contract is tested in Remix, the Ethereum Integrated Development Environment, primarily to evaluate contract deployment and NFT minting expenses. We focus on testing the mintNFT function in line with our research objectives. Leveraging the existing design of the internal calculation function helps pinpoint transaction costs to the mintNFT function since it invokes the calculation function.

Experimental results in Figure 5 indicate reasonable gas costs for NFT minting transactions. The higher contract deployment cost is justified as it involves interaction with the entire blockchain network, not just individual blocks. The successful execution of this contract in Remix demonstrates its suitability for deployment on the blockchain. Further enhancements by developers can enhance its security and functionality for pricing NFTs in various conditions.

5. Conclusion

This paper introduces a novel mechanism for pricing NFTs based on the rarity scores of features within a specific NFT collection. Grounded in the hedonic model framework and drawing inspiration from various NFT collections, our pricing model utilizes regression outcomes to create a corresponding contract. The successful execution of this contract demonstrates its potential as an alternative pricing solution, contributing to the standardization of NFT prices. We also conducted a comparative evaluation of our model, highlighting the role of factor analysis. Our future research

TABLE 4. HEDONIC MODEL PERFORMANCE

	HV-MTL	HV-MTL with Common Factors	Sappy Seal	Sappy Seal with Common Factors
$\mathbf{R^2}$	0.251	0.27	0.487	0.46
MAE	0.535	0.518	0.056	0.067
MSE	2.149	1.076	0.02	0.021
RMSE	1.466	1.037	0.141	0.144
MSD	-0.014	0.064	0.006	0.002
MAPE	0.254	0.244	0.094	0.122
Adjusted $\mathbf{R^2}$	0.251	0.27	0.487	0.46

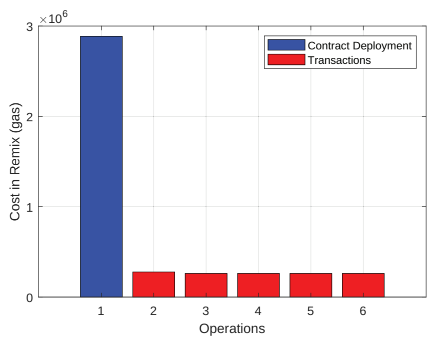

Figure 5. The gas cost associated with the proposed smart contract deployment and transactions in Remix.

will focus on expanding and improving the model's scope and applicability to address these challenges.

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References

[1] Wanxin Li, Collin Meese, Hao Guo, and Mark Nejad. Aggregated zero-knowledge proof and blockchain-empowered authentication for autonomous truck platooning. *IEEE Transactions on Intelligent Transportation Systems*, 2023.

[2] Hao Guo, Collin Meese, Wanxin Li, Chien-Chung Shen, and Mark Nejad. B 2 sfl: A bi-level blockchained architecture for secure federated learning-based traffic prediction. *IEEE Transactions on Services Computing*, 2023.

[3] Matthieu Nadini, Laura Alessandretti, Flavio Di Giacinto, Mauro Martino, Luca Maria Aiello, and Andrea Baronchelli. Mapping the nft revolution: market trends, trade networks, and visual features. *Scientific reports*, 11(1):20902, 2021.

[4] Christopher Yencha. Spatial heterogeneity and non-fungible token sales: Evidence from decentraland land sales. *Finance Research Letters*, page 103628, 2023.

[5] Amin Mekacher, Alberto Bracci, Matthieu Nadini, Mauro Martino, Laura Alessandretti, Luca Maria Aiello, and Andrea Baronchelli. Heterogeneous rarity patterns drive price dynamics in nft collections. *Scientific reports*, 12(1):13890, 2022.

[6] Howard Zhong and Mark Hamilton. Exploring gender and race biases in the nft market. *Finance Research Letters*, 53:103651, 2023.

[7] Nicola Borri, Yukun Liu, and Aleh Tsyvinski. The economics of non-fungible tokens. *Available at SSRN 4052045*, 2022.

[8] Arnav Kapoor, Dipanwita Guhathakurta, Mehul Mathur, Rupanshu Yadav, Manish Gupta, and Ponnurangam Kumaraguru. Tweetboost: Influence of social media on nft valuation. In *Companion Proceedings of the Web Conference 2022*, pages 621–629, 2022.

[9] Junliang Luo, Yongzheng Jia, and Xue Liu. Understanding nft price moves through social media keywords analysis. *arXiv preprint arXiv:2209.07706*, 2022.

[10] Christian Urom, Gideon Ndubuisi, and Khaled Guesmi. Dynamic dependence and predictability between volume and return of non-fungible tokens (nfts): The roles of market factors and geopolitical risks. *Finance Research Letters*, 50:103188, 2022.

[11] Sina Osivand and Hanieh Abolhasani. 'effect of bitcoin and etherium on non-fungible token (nft). *IOSR Journal of Business and Management*, 23(9):49–51, 2021.

[12] Christian Pinto-Gutiérrez, Sandra Gaitán, Diego Jaramillo, and Simón Velasquez. The nft hype: what draws attention to non-fungible tokens? *Mathematics*, 10(3):335, 2022.

[13] De-Rong Kong and Tse-Chun Lin. Alternative investments in the fintech era: The risk and return of non-fungible token (nft). *Available at SSRN 3914085*, 2021.

[14] Lennart Ante. Non-fungible token (nft) markets on the ethereum blockchain: Temporal development, cointegration and interrelations. *Economics of Innovation and New Technology*, pages 1–19, 2022.

[15] William Entriken, Dieter Shirley, Jacob Evans, and Nastassia Sachs. Eip-721: Erc-721 non-fungible token standard. *Ethereum Improvement Proposals*, 721, 2018.

[16] Brian Sanya Mondoh, Sara M Johnson, Matthew Green, and Aris Georgopoulos. Nft legal and regulatory compliance: Connoisseurship and critique. *Aris (Aristeidis), NFT Legal and Regulatory Compliance: Connoisseurship and Critique (November 12, 2022)*, 2022.

[17] Hongyu Guo, Mao Chen, and Wei Ou. A lightweight nft auction protocol for cross-chain environment. In *International Conference on Machine Learning for Cyber Security*, pages 133–146. Springer, 2022.

[18] Sherwin Rosen. Hedonic prices and implicit markets: product differentiation in pure competition. *Journal of political economy*, 82(1):34–55, 1974.

[19] Luisa Schaar and Stylianos Kampakis. Non-fungible tokens as an alternative investment: Evidence from cryptopunks. *The Journal of The British Blockchain Association*, 2022.

[20] Kin-Hon Ho, Yun Hou, Tse-Tin Chan, and Haoyuan Pan. Analysis of non-fungible token pricing factors with machine learning. In *2022 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pages 1161–1166. IEEE, 2022.

[21] Xi Zheng. Multimodal learning for improved nft price prediction. In *2022 IEEE International Conference on e-Business Engineering (ICEBE)*, pages 74–79. IEEE, 2022.

[22] Jerome Branny, Rolf Dornberger, and Thomas Hanne. Non-fungible token price prediction with multivariate lstm neural networks. In *2022 9th International Conference on Soft Computing & Machine Intelligence (ISCMI)*, pages 56–61. IEEE, 2022.

[23] Ran Ma, Xiaotian Yang, and Fei Gao. Non-fungible token forecast based on lstm. In *2022 4th International Conference on Applied Machine Learning (ICAML)*, pages 81–84. IEEE, 2022.

[24] Roman Kräussl and Alessandro Tugnetti. Non-fungible tokens (nfts): A review of pricing determinants, applications and opportunities. *Center for Financial Studies Working Paper*, (693), 2023.

[25] Joseph F Hair. Multivariate data analysis. 2009.