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Non-Fungible Tokens: What Makes Them Valuable?

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***Abstract*—Non-Fungible Tokens (NFTs) have revolutionized various industries and aspects of the digital world in several ways. Built on blockchain technology, NFTs provide a secure and transparent way to establish ownership and provenance of unique digital or physical items. This has wide-ranging implications, from art and collectibles to virtual real estate and digital goods. While NFTs offer many benefits, however, they also raise concerns, including environmental impacts due to energy-intensive blockchain networks, copyright and plagiarism issues, and speculative bubbles in the NFT market. In this work, we collected 200,000 tweets about NFTs and employed state-of-the-art neurosymbolic AI tools to better understand what are the online conversation drivers and sentiments around NFTs and, hence, gain insights about what makes them valuable.**

***Index Terms*—Non-Fungible Tokens, Digital Assets, Blockchain Technologies, NLP, Sentiment Analysis**

I. Introduction

Non-Fungible Tokens (NFTs) are a type of digital asset that represent ownership or proof of authenticity of a unique item or piece of content using blockchain technology. Unlike cryptocurrencies such as Bitcoin or Ethereum, which are fungible and can be exchanged on a one-to-one basis, NFTs are non-fungible, meaning each token is distinct and cannot be exchanged on a like-for-like basis with another NFT.

NFTs are used to represent one-of-a-kind digital or physical assets. This can include digital art, music, collectibles, virtual real estate, video clips, in-game items, and more. Each NFT has a distinct value and metadata that makes it unique. NFTs are typically built on blockchain platforms like Ethereum, Binance Smart Chain, or others. The blockchain serves as a decentralized and transparent ledger that records ownership and transaction history, ensuring the provenance and authenticity of the NFT.

Probably the best quality about NFTs is that they provide a way to establish and verify ownership of digital or physical assets: the blockchain records the history of ownership transfers, making it difficult to counterfeit or forge NFTs. Moreover, NFTs can be bought, sold, and traded on various online marketplaces and platforms. They are designed to be interoperable, meaning you can use an NFT purchased on one platform in a different application or marketplace.

Fig. 1. Top 10 most expensive NFTs ever sold, from CoinGecko https://coingecko.com/research/publications/10-most-expensive-nfts-ever-sold updated on September 17 2023.

Society is becoming increasingly digitalized due to the widespread adoption of digital technologies and the Internet. NFTs represent a novel way to assign and transfer ownership of assets in digital worlds. They have the potential to disrupt traditional industries, offering new opportunities for creators, collectors, and investors, but they also pose challenges and ethical considerations that need to be carefully addressed as their adoption continues to grow.

Speculation around NFTs has been a prominent aspect of their rise and popularity. Many individuals have viewed NFTs as investment opportunities, hoping to purchase NFTs at a lower price and sell them later for a higher price. This speculative behavior has been driven by stories of NFTs selling for astronomical sums, attracting investors seeking quick profits.

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NFTs in the art and collectibles space have also seen significant speculation. High-profile sales of digital artworks and collectibles have garnered media attention, fueling the perception that NFTs in this category can appreciate rapidly. Market hype and fear of missing out (FOMO) have also played a role in NFT speculation. As certain NFTs gain attention and value, others rush to join the market, hoping to capture similar gains. NFT markets, however, have experienced considerable price volatility, with the value of some NFTs fluctuating dramatically over short periods.

In this work, we carry out a preliminary investigation on Twitter data to study the reasons for such volatility but also to understand how investors and people in general associate value to NFTs. In particular, we collect 200,000 tweets about NFTs and employ state-of-the-art neurosymbolic AI tools to discover online conversation drivers and sentiments around NFTs and, hence, gain insights about what makes them valuable.

The remainder of this paper is organized as follows: Section II introduces our data collection methodology; Section III describes the data analysis approach undertaken; Section IV discusses results; finally, Section V offers concluding remarks and outlines future work.

II. Data Collection

We collected our NFT dataset from Twitter using the 15 hashtags listed below. We used the new Twitter Pro API package (priced at $5,000 per month) for one month between 1st June to 1st July 2023.

- `#NFT`: The most straightforward and widely used hashtag for all things related to NFTs.
- `#CryptoArt`: Often used for NFTs related to digital art and artists in the crypto space.
- `#NFTCommunity`: Used to engage with and connect to the broader NFT community.
- `#DigitalArt`: Specifically used for NFTs and digital art discussions and sharing.
- `#Collectibles`: Related to NFTs that are collectible items, such as trading cards and virtual collectibles.
- `#NFTsForGood`: Focused on NFTs used for charitable purposes or social causes.
- `#NFTInvesting`: For discussions about investing in NFTs, their potential returns, and market trends.
- `#Blockchain`: General discussions about blockchain technology, which underpins NFTs.
- `#Metaverse`: Used for NFTs and discussions related to virtual worlds and metaverse projects.
- `#CryptoCollectibles`: Similar to #Collectibles, but specifically focused on NFTs within the cryptocurrency space.
- `#NFTArtist`: Used by artists who create and sell NFTs to promote their work.
- `#NFTMarketplace`: Discussions about platforms where NFTs are bought and sold, such as OpenSea, Rarible, and others.
- `#CryptoTwitter`: Not exclusively for NFTs but often includes NFT-related discussions within the broader crypto community.
- `#NFTAuctions`: Used when discussing NFTs that are being auctioned off to the highest bidder.
- `#NFTDrop`: Refers to the release of new NFT collections or drops by artists or creators.

Within one month, we collected a total of 1,000,000 tweets. After pre-processing (e.g., removal of irrelevant tweets, removal of non-English tweets, removal of duplicates, removal of re-tweets, etc.), we were left with one fifth of it. The exact distribution of tweets with respect to hashtags is illustrated in Table I.

Hashtag	Start Date	End Date	Tweet Count
#NFT	01-06-2023	01-07-2023	89,091
#CryptoArt	01-06-2023	01-07-2023	24,672
#NFTCommunity	01-06-2023	01-07-2023	13,137
#DigitalArt	01-06-2023	01-07-2023	9,062
#Collectibles	01-06-2023	01-07-2023	8,913
#NFTsForGood	01-06-2023	01-07-2023	8,360
#NFTInvesting	01-06-2023	01-07-2023	7,118
#Blockchain	01-06-2023	01-07-2023	7,093
#Metaverse	01-06-2023	01-07-2023	6,220
#CryptoCollectibles	01-06-2023	01-07-2023	5,916
#NFTArtist	01-06-2023	01-07-2023	5,028
#NFTMarketplace	01-06-2023	01-07-2023	4,808
#CryptoTwitter	01-06-2023	01-07-2023	4,713
#NFTAuctions	01-06-2023	01-07-2023	3,062
#NFTDrop	01-06-2023	01-07-2023	2,807
			Total: *200,000*

TABLE I
Distribution of collected tweets with respect to hashtags.

Fig. 2 proposes a visual representation of the most significant terms in the collected dataset (after stopword removal), where the size of each word is proportional to its frequency.

Fig. 2. Word cloud representing the top keywords in the dataset.

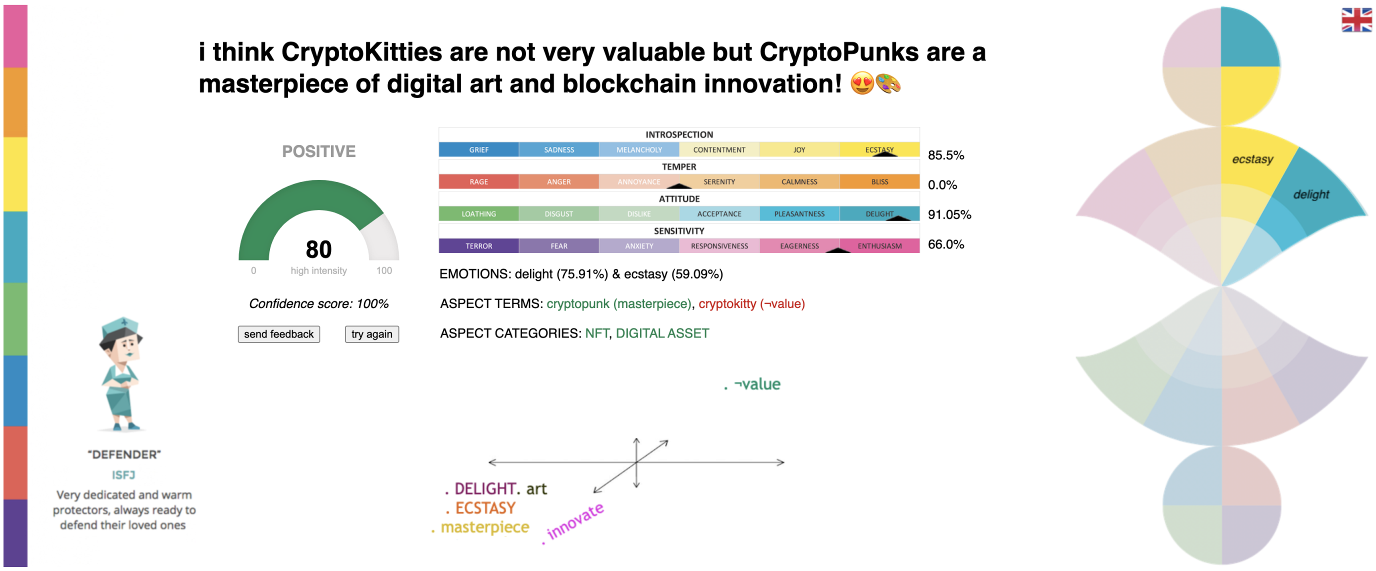

Fig. 3. Sentic API user interface sample.

III. Data Analysis

In order to facilitate the automated extraction of valuable insights from the collected data, we leverage sentiment analysis, a natural language processing (NLP) field in which computational methods are leveraged to determine the polarity or emotional tone expressed in a piece of text [1], [2]. Different AI techniques have been leveraged to improve both accuracy and interpretability of sentiment analysis algorithms, including symbolic AI [3], [4], subsymbolic AI [5], [6], and neurosymbolic AI [7], [8]. Besides traditional algorithms [9] focusing on English text, multilingual [10], [11] and multimodal [12], [13] sentiment analysis have also attracted increasing attention recently. Typical applications of sentiment analysis include social network analysis [14], finance [15], and healthcare [16]. In this work, we use Sentic APIs[1], a suite of application programming interfaces, which employ neurosymbolic AI to perform various sentiment analysis tasks in a fully interpretable manner (Fig. 3). A short description of each API and its usage within this work is provided in the next 12 subsections.

A. Concept Parsing

This API provides access to Sentic Parser [17], a knowledge-specific concept parser based on SenticNet [18], which leverages both inflectional and derivational morphology for the efficient extraction and generalization of affective multiword expressions from English text. In particular, Sentic Parser is a hybrid semantic parser that uses an ensemble of constituency and dependency parsing and a mix of stemming and lemmatization [19] to extract 'semantic atoms' like pain_killer, go_bananas, or get_along_with, which would carry different meaning and polarity if broken down into single words (Fig. 4).

[1]https://sentic.net/api

We use the API for extracting words and multiword expressions from tweets in order to better understand what are the key concepts related to NFTs. As shown in Fig. 3, for example, the concepts extracted are art, masterpiece, innovate, and value.

B. Subjectivity Detection

Subjectivity detection is an important NLP task that aims to filter out 'factual' content from data, i.e., objective text that does not contain any opinion. This API leverages a knowledge-sharing-based multitask learning framework powered by a neural tensor network, which consists of a bilinear tensor layer that links different entity vectors [20].

We use the API to classify NFT-related tweets as either objective (unopinionated) or subjective (opinionated) but also to handle neutrality, that is, a tweet that is opinionated but neither positive nor negative (ambivalent stance towards the opinion target). All labels come with a confidence score based on how much SenticNet concepts contributed to the classification output. As shown in Fig. 3, for example, the confidence score is 100%.

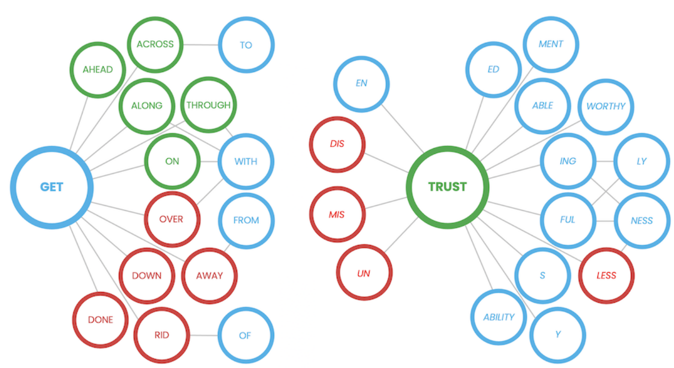

Fig. 4. Sentic Parser graph sample.

C. Polarity Classification

Once an opinionated tweet is detected using the *Subjectivity Detection API*, the *Polarity Classification API* further categorizes this tweet as either positive or negative. This is one of the most important APIs we use to understand the stance of tweeters towards NFTs. It leverages an explainable fine-grained multiclass sentiment analysis method [21], which involves a multi-level modular structure designed to mimic natural language understanding processes, e.g., ambivalence handling process, sentiment strength handling process, etc. As shown in Fig. 3, for example, the extracted polarity is POSITIVE.

D. Intensity Ranking

For a finer-grained analysis, we further process the NFT tweets classified by the *Polarity Classification API* using the *Intensity Ranking API* to infer their degree of negativity (floating-point number between -1 and 0) or positivity (floating-point number between 0 and 1). In particular, the API leverages a stacked ensemble method for predicting sentiment intensity by combining the outputs obtained from several deep learning and classical feature-based models using a multi-layer perceptron network [22]. As shown in Fig. 3, for example, the extracted polarity is 80 (high intensity).

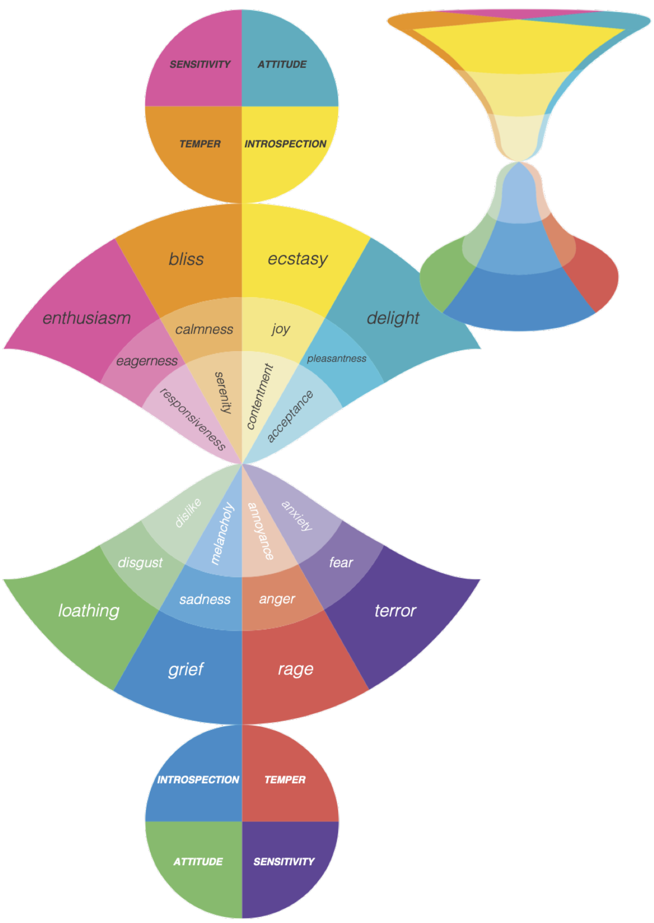

Fig. 5. The Hourglass of Emotions.

E. Emotion Recognition

This API employs the Hourglass of Emotions [23], a biologically-inspired and psychologically-motivated emotion categorization model, that represents affective states both through labels and through four independent but concomitant affective dimensions, which can potentially describe the full range of emotional experiences that are rooted in any of us (Fig. 5).

We use the API to go beyond polarity and intensity by examining what are the specific emotions elicited by NFTs in both their ardent supporters and vocal opposers. As shown in Fig. 3, for example, the emotion spectrum of the input is visualized in terms of the Hourglass Model's affective dimensions, namely: +91.05% Attitude, +85.5% Introspection, and +66% Sensitivity. From these, the API also extracts the two top resulting emotion labels, delight and ecstasy, with an intensity of 75.91% and 59.09%, respectively.

F. Aspect Extraction

This API uses a meta-based self-training method that leverages both symbolic representations and subsymbolic learning for extracting aspects from text. In particular, a teacher model is trained to generate in-domain knowledge (e.g., unlabeled data selection and pseudo-label generation), where the generated pseudo-labels are used by a student model for supervised learning. Then, a meta-weighter is jointly trained with the student model to provide each instance with sub-task-specific weights to coordinate their convergence rates, balancing class labels, and alleviating noise impacts introduced from self-training [24].

We use the API to better understand the NFT phenomenon in terms of subtopics or opinion targets. Instead of simply identifying a polarity associated with the whole tweet, the *Aspect Extraction API* deconstructs input text into a series of specific aspects or features to then associate a polarity to each of them. This is particularly useful to process antithetic tweets, e.g., tweets where users list pros and cons of NFTs. As shown in Fig. 3, for example, the aspect terms extracted are cryptopunk and cryptokitty, which belong to the aspect categories NFT and DIGITAL ASSET.

G. Personality Prediction

This API uses a novel hard negative sampling strategy for zero-shot personality trait prediction from text using both OCEAN and MBTI models (Fig. 6). In particular, the API leverages an interpretable variational autoencoder sampler, to pair clauses under different relations as positive and hard negative samples, and a contrastive structured constraint, to disperse the paired samples in a semantic vector space [25].

We use the API to study the different personalities and personas involved in NFT discussions and, hence, better understand the possible drivers of such discussions. As shown in Fig. 3, for example, the MBTI personality extracted is ISFJ (Introversion, Sensing, Feeling, and Judging).

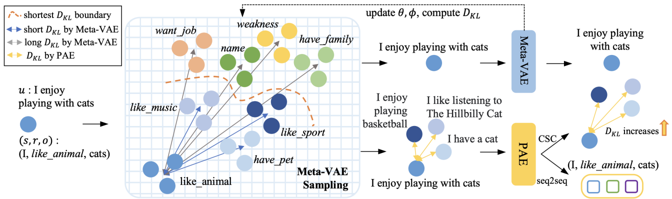

Fig. 6. Personality prediction visualization sample.

H. Sarcasm Identification

This API combines commonsense knowledge and semantic similarity detection methods to better detect and process sarcasm in text. It also employs a contrastive learning approach with triplet loss to optimize the spatial distribution of sarcastic and non-sarcastic sample features [26]. We use the API to understand how much NFTs are subject to satire and critique but also to increase the accuracy and reliability of the *Polarity Classification API*. As sarcasm often involves expressing a sentiment that is opposite to the intended emotion, in fact, it may lead to polarity misclassification and, hence, generate wrong insights and conclusions.

I. Depression Categorization

This API employs ensemble hybrid learning methods for automated depression categorization. In particular, the API combines symbolic AI (lexicon-based models) with subsymbolic AI (attention-based deep neural networks) to enhance the overall performance and robustness of depression detection [27]. We use it to study different reactions to NFT devaluations and depreciations by different users, e.g., those experiencing emotional distress or psychological challenges related to their NFT portfolio.

J. Toxicity Spotting

Given the controversy associated with digital assets, it is important to measure the different types and intensities of toxicity associated with some NFT tweets. This API is based on a multichannel convolutional bidirectional gated recurrent unit for detecting toxic comments in a multilabel environment [28]. In particular, the API extracts local features with many filters and different kernel sizes to model input words with long term dependency and then integrates multiple channels with a fully connected layer, normalization layer, and an output layer with a sigmoid activation function for predicting multilabel categories such as ‘obscene’, ‘threat’, or ‘hate’.

K. Engagement Measurement

Measuring engagement is important to understand which specific topics or events, e.g., NFT drops, are more impactful for both NFT enthusiasts and skeptics. This API employs a graph-embedding model that fuses heterogeneous data and metadata for the classification of engagement levels. In particular, the API leverages hybrid fusion methods for combining different types of data in a heterogeneous network by using semantic meta paths to constrain the embeddings [29].

L. Well-being Assessment

Besides levels of toxicity and engagement, another important dimension for understanding NFT tweeters is their level of stress, e.g., anxiety caused by FOMO. This API leverages a mix of lexicons, embeddings, and pretrained language models for stress detection from social media texts [30]. In particular, the API employs a transformer-based model via transfer learning to capture the nuances of natural language expressions that convey stress in both explicit and implicit manners.

IV. Results

In this section, we discuss the most important insights gained through the use of Sentic APIs on the collected dataset. The *Concept Parsing API* enabled us to discover what are the current hot topics related to NFTs. Below are some of the most frequent concepts (words and multiword expressions) parsed.

- blockchain
- gaming
- digital_art
- ethereum
- crypto_collectibles
- decentralized
- smart_contract
- cryptocurrency
- tokenization
- metaverse
- token_standard
- erc_721
- erc_1155
- rarity
- ownership
- marketplace
- defi
- decentralized_finance
- ip_right
- nft_drop
- virtual_real_estate
- digital_ownership
- authentication
- copyright
- royalties
- secondary_market
- opensea
- rarible
- crypto_art
- nft_wallet
- pfp
- profile_picture_nft
- dao
- art_provenance
- virtual_goods
- minting_nft
- cryptopunks
- crypto_kitties
- token_supply
- virtual_world

Through the *Subjectivity Detection API*, we realized that the vast majority of NFT tweets were opinionated. The unopinionated tweets were mostly promotional and advertising posts. By processing subjective text using the *Polarity Classification API*, we then realized that the number of NFT enthusiasts is far greater than the number of NFT detractors (at least for the time window of our analysis). For the former group, the most common MBTI personality type was ISTP and the predominant emotion was enthusiasm. The latter group (the naysayers), instead, was characterized by an INTJ personality trait and a predominant emotion of fear.

Finally, the most useful insights came from the *Aspect Extraction API*, which helped us individuate the key features of NFTs that make them valuable in the eyes of investors and the wider NFT community. We list the 10 most frequent ones below along with a short elucubration on why such aspects emerged from the 200,000 tweets as the most prominent.

- `Rarity`: NFTs are unique, and their scarcity is a significant driver of value. The rarer an NFT is, the more valuable it tends to be. This can be due to the limited edition of a digital artwork, a unique in-game item, or a one-of-a-kind collectible.
- `Reputation`: The reputation and popularity of the creator or artist behind the NFT can greatly influence its value. Established artists, musicians, and influencers often command higher prices for their NFTs due to their existing fan base and followers.
- `Authenticity`: NFTs provide proof of authenticity and ownership on the blockchain, which adds value by ensuring that the digital or physical asset associated with the NFT is genuine and has a clear ownership history.
- `Significance`: Some NFTs gain value because they are associated with historically significant moments, events, or trends in the digital or real world. For example, the first-ever tweet or a memorable digital artwork may have added value due to their historical context.
- `Utility`: NFTs that have utility or use within a specific ecosystem or application can be more valuable. For example, NFTs that grant access to virtual worlds, games, or exclusive content can have practical value beyond being collectibles.
- `Interoperability`: NFTs that can be used in multiple applications or platforms tend to have higher value because they have a broader range of potential uses and can attract a larger user base.
- `Demand`: The demand for a particular NFT within a passionate and active community can significantly drive up its value. Online communities and social media platforms play a role in creating hype and demand around specific NFTs.
- `Provenance`: A clear and well-documented ownership history, especially if the NFT has passed through the hands of notable collectors or investors, can enhance its value and credibility.
- `Royalties`: NFTs that offer royalties to the original creator on secondary sales can be more attractive to creators, which can lead to higher prices.
- `Hype`: Market sentiment, hype, and speculative behavior can temporarily inflate the value of certain NFTs, leading to rapid price increases. However, these factors can also contribute to market volatility.

V. Conclusion

NFTs have sparked innovation and transformed various industries by creating new opportunities for creators, collectors, and investors. Their impact continues to evolve, and their future role in the digital economy remains a subject of exploration and debate.

In this study, we gathered 200,000 tweets discussing NFTs and utilized cutting-edge neurosymbolic AI tools to enhance our comprehension of the factors influencing online conversations and sentiments related to NFTs.

Our objective was to glean insights into the factors contributing to their perceived value. Through Sentic APIs we discovered the following 10 key aspects: rarity, reputation, authenticity, significance, utility, interoperability, demand, provenance, royalties, and hype. Future work will focus on conducting controlled experiments to investigate how such aspects influence the perceived value of NFTs, e.g., by manipulating rarity or reputation to assess their impact on the willingness of buyers to pay for an NFT.

Finally, it is important to note that NFT values can be highly subjective and may fluctuate over time. What one person values as a unique and valuable NFT, another may not. Additionally, the NFT market is still relatively new and evolving, and its dynamics can be influenced by trends and market sentiment. As with any investment, potential buyers should conduct thorough research and due diligence before purchasing NFTs.

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