Using sentiment analysis on Tweets to assess its usefulness for price and purchase signal estimation: A case study of an NFT artwork

Master Thesis submitted in fulfillment of the Degree

Master of Science

in Sustainable Development, Management and Policy

Submitted to Dr. Christian Weismayer

Sepehr Ghaffari

62004297

Vienna, 20.06.2023

AFFIDAVIT

I hereby affirm that this Master's Thesis represents my own written work and that I have used no sources and aids other than those indicated. All passages quoted from publications or paraphrased from these sources are properly cited and attributed.

The thesis was not submitted in the same or in a substantially similar version, not even partially, to another examination board and was not published elsewhere.

6/21/2023	Sepehr Ghaffari
Date	Signature

ABSTRACT

The Non-Fungible Token (NFT) market has arisen as a significant area of interest in the fast-expanding digital ecosystem. This thesis goes deep into the core of the digital revolution, investigating the complex interaction between public sentiment and the NFT market. The study adopts a methodical technique that begins with keyword selection and progresses to the extraction and analysis of social media material and financial data on NFTs. The project largely extracts data from Twitter, utilizing an academic-level API to obtain a vast number of data. The study's objectives, particularly the goal of identifying significant relationships and patterns in the collected data, influenced the research design. The datasets were gathered from reliable sources, and the variables of interest and data extraction techniques were thoroughly explained. The study's findings show substantial relationships between various feelings and the market capitalization of NFTs. The study discovered that joy and disgust have the strongest inverse connections with market capitalization. Furthermore, the overall number of sentiments is positively connected with market capitalization. The study also included the development and testing of time series models for market forecasting. The study's goal is to gain a better understanding of the impact of mood on the NFT market. The findings of this study could be useful in formulating future tactics for NFT market participants and laying the groundwork for additional academic research in this sector.

ACKNOWLEDGEMENTS

I am greatly touched to convey my gratitude to all who have been essential in the completion of my thesis for their unwavering support and encouragement. It would have been hard to manage this path without you alongside me.

My wife, or rather, my best friend, Elmira, has been at the center of my journey. More than a decade of unflinching love and support has lit the journey we've taken together. Even in the darkest of circumstances, your reassuring presence has been a continuous lighthouse for me. Words could never explain how grateful I am to you, my sweet Elmira.

My warmest thanks go to my supervisor, Christian Weismayer, who proved to be more reliable than even the most well-documented R package. At every point, your prompt replies and invaluable solutions were critical. Your extensive knowledge and skilled advice were like a lighthouse, guiding me safely to land in the wide sea of research.

Afra, my darling sister, deserves a heartfelt thank you. Her consistent help has been a lifeline more times than she can count. Her unending compassion and steadfast faith in me have been pillars of strength on which I have relied throughout this journey. I'm sure she has supported me more than I even know.

Jalil Rezagholizadeh, the fortress in the storm, deserves my appreciation as well. This achievement would not have been achievable without your unwavering support. You were there for me every step of the journey, offering me reassurance and support.

I'd like to thank all of the unidentified individuals who made this research possible through their tweets. You've done more than just express your emotions; you've turned them into a spark for comprehension and discovery.

Finally, a heartfelt salute to my beloved cat, Lecker. Your innocent and happy frolics around the house have provided a welcome respite from the frequently laborious work of thesis writing. You have been a beautiful ray of sunshine in my life, effortlessly making my problems lighter.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ANN: Artificial Neural Networks

AWS: Amazon Web Services

BAYC: Bored Ape Yacht Club

BSC: Binance Smart Chain

CAGR: Compound Annual Growth Rate

CNN: Convolutional Neural Networks

DAOs: Decentralized Autonomous Organizations

dApps: Decentralized Applications

DeFi: Decentralized Finance

DJIA: Dow Jones Industrial Average

DPoS: Delegated Proof of Stake

EmoLex: NRC Emotion Lexicon

ERC: Ethereum Request for Comment

ETH: Ether

GAAP: Generally Accepted Accounting Principles

GPOMS: Google-Profile of Mood States

ICOS: Initial Coin Offerings

IP: Intellectual Property

IPFS: InterPlanetary File System

LIWC: Linguistic Inquiry and Word Count

MAYC: Mutant Ape Yacht Club

mBERT: Multilingual BERT

MC: Market Capitalization

Mturk: Amazon's Mechanical Turk

NFT: Non-Fungible Token

NLP: Natural Language Processing

NRC: National Research Council (Canada)

PFP: Profile Picture

PoS: Proof of Stake

PoW: Proof of Work

RNN: Recurrent Neural Networks

SOL: Solana

SVM: Support Vector Machines

VAR: Vector Autoregression Model

1 INTRODUCTION

Non-fungible tokens (NFTs) are digital assets that are revolutionizing how we perceive ownership, value, and community in the digital space. The market for NFTs, which was valued at $250 million in 2020, exploded to $24.9 billion in 2021, demonstrating the meteoric ascent of this disruptive technology (Figure 1-1) (D'Onfro, 2021). By tokenizing digital and physical assets, NFTs have transformed numerous industries, including art, gaming, music, and real estate, thereby offering creators, collectors, and investors unique opportunities (Treiblmaier, 2023). Pak's batch of NFTs is the most expensive NFTs ever constructed. Merge began with 29,000 tokens. Currently has fewer than 250,000 inhabitants. Collectors and investors rallied in support of Pak's NFT artwork 'The Merge', raising nearly 92 million USD[1] ("The Most Expensive NFTs in History - Bankless Publishing," 2023).

[1] Merge is a compilation of NFTs designed by digital artist Pak. It is distinct from other digital compositions in that it contains interactive NFTs. This might clarify why it is the world's most expensive NFT. The collection's images are a compilation of white or yellow circles on a black background. When Pak placed Merge up for auction, it was comprised of 312,686 NFTs, also known as mass units. Each purchaser may purchase as many units of mass as desired; nevertheless, only one NFT may be held. Pak created Merge on a platform, permitting each cryptocurrency wallet to hold a single NFT. Therefore, if one already possesses a unit of mass and purchases another, the wallet will not indicate ownership of two units of mass. Instead, the second mass unit will combine with the first mass unit to produce a new, larger mass unit. The platform operates using a system comparable to the cryptographic combustion mechanism. It eliminates coinage from circulation permanently, reducing their availability. In the event of the Merge, the platform will determine if an NFT exists in a buyer's wallet. If a wallet contains an NFT, the lesser NFT will merge with the larger one. Regardless of the increase in mass of individual components when combined, the collection's total mass remains unchanged. In addition, the total number of mass units available for purchase decreases with each mass unit transferred to a wallet containing mass. Consequently, each unit can be stored in a single wallet, making Merge one piece of mass, or NFT.

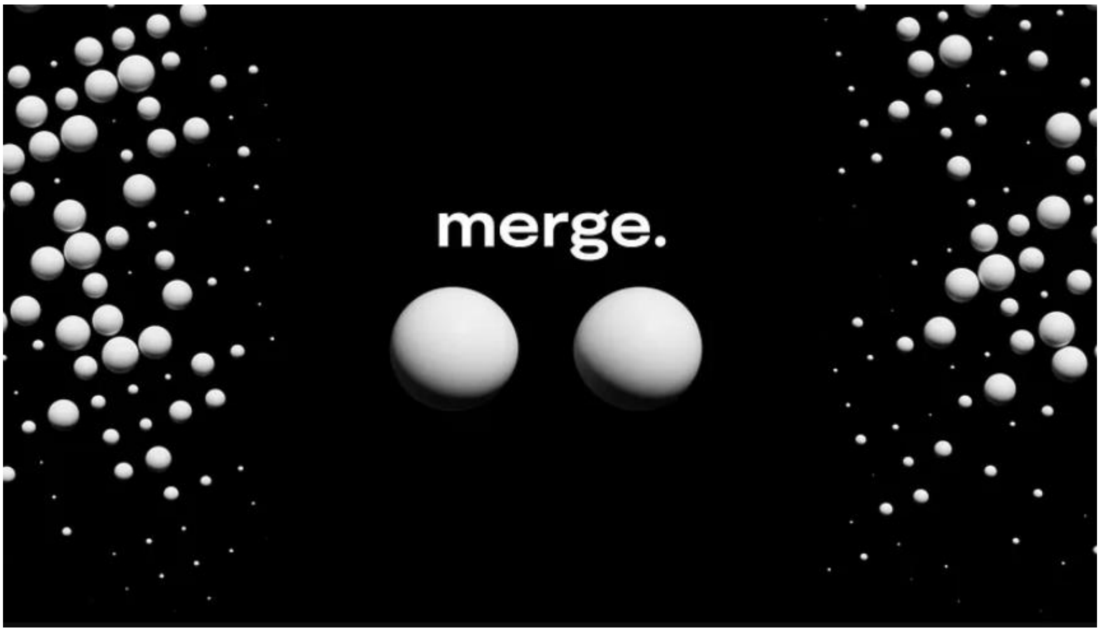

FIGURE 1-1- THE MERGE NFT (“The Most Expensive NFTs in History - Bankless Publishing,” 2023)

The Merge is one example of successful gamification through NFTs indicating the significance of the subjective value by the collectors. The concept of sentimental analysis and the role of social media interactions in determining the value of non-fungible tokens are central to their valuation. Recent studies have examined the impact of platforms such as OpenSea and Twitter on NFT valuation (Nadini et al., 2021). Their research has demonstrated that social media characteristics have a significant impact on the value of digital assets. This emphasizes the significance of community-based value and the philosophy underlying creator-centered and observer-centered valuations of NFTs.

Understanding the intricate dynamics between the creator, the observer, and the larger community becomes increasingly important as we progress further into the digital domain. The creator-centered value of NFTs resides in their capacity to empower artists and creators by granting them control over their work, providing them with a direct connection to their audience, and assuring equitable compensation through royalties (Et John, 2021). Observer-centered value, on the other hand, arises from the subjective perception and sense of attachment that collectors and observers form with digital assets, frequently influencing the demand and price of NFTs (Caxton et al., 2022).

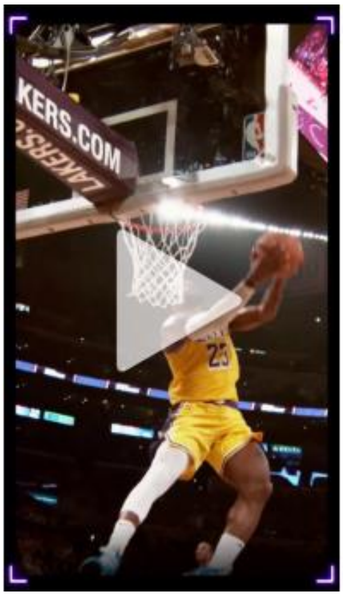

FIGURE 1-2- NBA TOP SHOT NFT: 2019-20 LEBRON JAMES DUNK

Digital art, collectibles platforms such as NBA Top Shot (Figure 1-2), and community-building initiatives such as Bored Ape Yacht Club (Figure 1-3) have spawned NFT ecosystems (Bao & Roubaud, 2021). These ecosystems generate value with NFTs by granting their holders access to a growing selection of products and experiences. Several well-known brands have introduced NFT series in an effort to strengthen and grow their existing communities. NFT initiatives must make meaningful use of the technology, leverage a community of users, sustain ongoing engagement, provide accessible on-ramps for new users, and withstand crypto market fluctuations in order to be successful. Uncertainty surrounds the future of NFTs, but their capacity to facilitate new markets and generate value through community engagement suggests at their potential impact (Kaczynski & Kominers, 2021).

FIGURE 1-3- ASSORTMENT OF BORED APE YACHT CLUB NFTS

This thesis intends to delve deeper into the world of non-fungible tokens by investigating the factors that contribute to their valuation, the role of sentimental analysis, and the impact of social media interactions on the NFT landscape. By analyzing the interaction between creators, observers, and the larger community, we hope to discover the underlying principles that govern the NFT market and its future course.

1.1 Problem statement

The rapid emergence of non-fungible tokens has ushered in a new domain of digital possibilities, revolutionizing industries such as art, gaming, music, and real estate (Nadini et al., 2021). With the increasing significance of community engagement and social media engagement in the valuation and perception of NFTs, it has become increasingly important to comprehend the impact of sentiments on NFT pricing. The NFT market is driven by creator-centered and observer-centered values, which can be substantially affected by the community and its interactions on social media networks (Et John, 2021).

Assessing the impact of sentiments conveyed in tweets on the valuation of NFTs and exploring the possibility of developing prediction models based on these sentiments constitutes the problem at hand. By examining the correlation between social media interactions and NFT valuations, it is essential to develop strategies that not only cultivate a deeper comprehension of the role of community in the NFT market, but also provide insights into the future pricing trends of NFTs (Dowling, 2022).

1.2 The study's objectives

The objective of this study is to bridge the gap between the NFT market and the significance of social media sentiment analysis in assessing the value of these digital assets, eventually contributing to the development of forecasting algorithms that can improve the understanding and adoption of NFTs in mainstream markets. Moreover, this thesis would be to evaluate the link between sentiments in tweets and their frequency with the price variation of specified NFTs. So, the tweets in specific periods containing NFT-related keywords will be gathered. The content of each will be analyzed through sentimental analysis. The quantity of specifically expressed emotions would act as the key measure. Following is the list of questions for this study:

RQ1: To what extent can sentiments on Tweets affect the financial performance of an NFT?

RQ2: Is there a difference in the relationship between different NFTs and their sentiments on Tweets between different NFTs?

In accordance with these research concerns, the null hypothesis is assumed as follows:

H0: None of the predictor variables will have significant impacts on the NFTs market price.

The predictor variables are the daily average sentiments for various NFTs. The outcome variables consist of the closing prices of various NFTs. Moreover, the following hypotheses will be presumed in light of the formulated research queries.

H1: Sentimentally positive tweets about specific NFT are accompanied by an increase in the price of that NFT.

H2: Sentimentally negative tweets about specific NFT are accompanied by a decrease in the price of that NFT.

1.3 Structure of thesis

This thesis is divided into six chapters, each of which focuses on a distinct aspect of the study, which seeks to evaluate the impact of sentiments conveyed in tweets on the valuation of non-fungible tokens (NFTs) and investigate the possibility of developing prediction models based on these sentiments.

1. *Introduction:* The first chapter gives an entertaining introduction to the NFT market, its relevance to social media interactions, and the significance of community involvement. It introduces the problem statement, which focuses on evaluating the influence of sentiments on NFT pricing and developing prediction models.
2. *Literature Review:* In the second chapter, existing research and studies on NFTs, sentiment analysis, and the effect of social media on asset value will be examined. This chapter will provide a comprehensive comprehension of the current state of

knowledge in the field and identify research deficiencies that will be addressed by the thesis.

3. *Methodology:* The third chapter will outline the research methodology, including the choice of keywords, the rationale behind each, the strategy for gathering data from Twitter, and the sentiment analysis procedure. The section will then cover sources of financial data on NFTs and statistical analysis using R.
4. *Analysis & Discussion:* The data extracted from the sources specified in the methodology chapter will be presented in the fourth chapter. This chapter will highlight the outcomes of sentiment analysis, financial data on NFTs, and R-based statistical analysis. The 4th chapter will go through the findings of the data analysis. It will endeavor to establish connections between current investor/consumer behavior and the study's findings. This discussion will shed light on the influence of sentiments on the pricing of NFTs and the possibility of developing prediction models.
5. *Conclusion:* The last chapter of the thesis will summarize the important results, examine the study's limitations, and recommend prospective future research directions in the area of NFTs and sentiment analysis.

This thesis seeks to contribute to the comprehension of the role of social media sentiment analysis in the valuation of NFTs and to provide helpful insights into the development of prediction models that can facilitate the adoption and growth of NFTs in mainstream markets.

2 LITERATURE REVIEW

2.1 Introduction

In recent years, sentiment analysis has emerged as a potent instrument for gleaning valuable insights from user-generated content, particularly on social media platforms like Twitter. With the increasing prevalence of non-fungible tokens in the world of crypto art, determining precise price and purchase signals has become a crucial aspect for investors, artists, and collectors. Having said that, using sentiment analysis methods on social media data, we aim to forecast variations in NFT pricing, offering significant insights into this emerging digital market. This literature review investigates the current body of research on employing different analysis techniques to evaluate the utility of varied data sources for estimating price and purchase signals in the context of an NFT artwork. The review is divided into the following five sections: (1) sentiment analysis techniques, (2) twitter as a data source, (3) blockchain technology, (4) NFT artwork market, and (5) sentiment analysis applications in NFT artwork pricing.

The initial part provides an overview of the various sentiment analysis methodologies, such as machine learning and lexicon-based approaches, along with their respective advantages and disadvantages.

The second section discusses Twitter's unique characteristics as a source of data for sentiment analysis, as well as the difficulties associated with processing and analyzing Tweets.

The third section introduces blockchain technology, concentrating on its key characteristics, including decentralization, transparency, and immutability. This section also examines the role of blockchain in facilitating the creation and trading of non-fungible tokens, which serve as digital certificates of possession for one-of-a-kind digital assets.

The fourth section examines the swiftly changing market for NFT artworks, including the factors influencing pricing and demand, as well as the impact of social media on the NFT landscape.

The fifth section concludes with a discussion of the application of sentiment analysis to determine price and purchase signals for NFT artwork. This section emphasizes pertinent case studies, empirical findings, and prospective avenues for future research, evaluating the efficacy of using sentiment analysis on Tweets to anticipate the pricing and demand for NFT artwork.

2.2 Sentiment analysis

Sentiment analysis, also referred to as opinion mining or sentiment AI, is a subfield of natural language processing (NLP) that seeks to automatically extract subjective information from textual data (Taboada, 2016). Due to the increasing accessibility of user-generated content on the internet and the rapid expansion of social media platforms, the technique has received considerable attention over the past two decades. The following section provides a comprehensive overview of sentiment analysis techniques, concentrating on their history, methods, languages, typical applications, and how social media can be leveraged to gain insight into financial markets.

2.2.1 History

Sentiment analysis has its origins in the field of NLP, which dates back to the 1950s with the creation of the first machine translation systems (Jones, 1994; Mielke et al., 2021). In the late 1990s and early 2000s, however, researchers began investigating techniques for extracting opinions and sentiments from textual data (Johri et al., 2021). Early works concentrated on document-level sentiment classification, frequently employing supervised machine learning techniques to classify movie or product reviews as positive, negative, or neutral. Sentiment analysis has expanded over time to include multiple levels of granularity (e.g., sentence, aspect, and entity level) and diverse application domains, such as politics, healthcare, and finance (Johri et al., 2021; Nadkarni et al., 2011).

As sentiment analysis continued to develop, researchers began to investigate various approaches and methods for analyzing emotion (Pang et al., 2002). Lexicon-based approaches, which rely on predefined sentiment inventories or lexicons to determine sentiment polarity, were introduced in the early 2000s. The development of rule-based methods, which integrate linguistic principles or heuristics to more accurately capture sentiment, enhanced these approaches (Kaur & Gupta, 2013).

During the middle of the 2000s, machine learning-based approaches acquired popularity, with researchers using algorithms such as Naive Bayes, support vector machines (SVM), and decision trees to create sentiment classifiers (Pang & Lee, 2004). These techniques allowed for a more sophisticated analysis of sentiment because they automatically learned sentiment patterns from labeled training data.

In the late 2000s and early 2010s, the emergence of social media platforms fueled the growth of sentiment analysis by providing a wealth of user-generated content rich in opinions and sentiments (C.-C. Chen et al., 2020). Researchers began to investigate the use of sentiment analysis for social media data, including tweets and Facebook posts, which led to the development of new techniques and tools tailored to the specific characteristics of these data sources (Pak & Paroubek, 2010).

Deep learning techniques, including convolutional neural networks (CNN) and recurrent neural networks (RNN), have emerged as potent instruments for sentiment analysis in recent years (Banerjee et al., 2019). By automatically learning feature representations from unprocessed text, these techniques offer enhanced performance, particularly on massive datasets. In addition, the introduction of transformer-based models, including BERT and GPT, has enabled more accurate and context-aware sentiment analysis across a variety of domains and languages (Tenney et al., 2019).

Nowadays, sentiment analysis is a well-established field of study with numerous applications in diverse disciplines, including business, marketing, healthcare, and politics. As the volume and diversity of textual data continue to expand, sentiment analysis techniques are anticipated to play an increasingly important role in gleaning valuable insights from this bounty of data.

2.2.2 Techniques

Techniques for sentiment analysis are computational methods employed to identify, extract, and quantify subjective information from textual data, such as opinions, sentiments, and attitudes. Various domains, such as marketing, finance, politics, and healthcare, use these techniques for evaluating user-generated content on social media platforms, reviews, and other forms of text data. There are three main categories of sentiment analysis techniques: lexicon-based, machine learning-based, and hybrid approaches (Sadia et al., 2018). Following flow chart summarize these techniques.

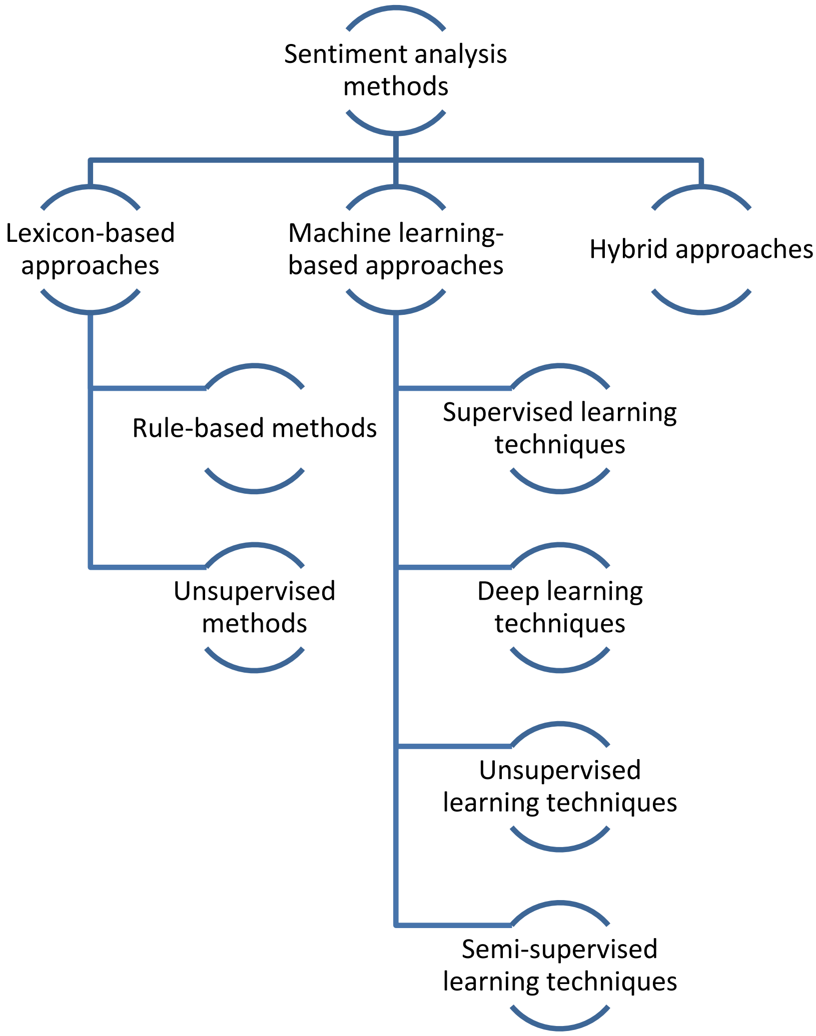

FIGURE 2-1- SENTIMENT ANALYSIS APPROACH

2.2.2.1 Lexicon-based approaches

These techniques rely on sentiment dictionaries or lexicons that contain collections of terms or phrases along with their associated sentiment scores or polarity designations (positive, negative, or neutral). In their 2013 study, Moraes, Valiati, and Neto suggest a lexicon-based sentiment analysis strategy using SentiWordNet to categorize movie evaluations at the document level. They compare the performance of their method to SVM and Artificial Neural Networks (ANN) (Moraes et al., 2013).

Using the SentiWordNet lexicon, the authors preprocess the movie evaluations and calculate sentiment scores for individual words. They then determine the overarching polarity of sentiment for the entire review. While the lexicon-based approach performs well, its classification accuracy is marginally lower than that of SVM and ANN, suggesting that machine learning techniques may provide enhanced performance for complex manifestations of emotion.

Lexicon-based methods can be further categorized as follows:

2.2.2.1.1 Rule-based methods

These techniques employ a predefined set of linguistic rules or heuristics to compute sentiment scores according to the sentiment values and grammatical relationships of individual words (KABORE, 2018).

2.2.2.1.2 Unsupervised methods

These techniques utilize statistical methods to aggregate sentiment scores in the absence of labeled training data (Sadia et al., 2018).

2.2.2.2 Machine learning-based approaches

These techniques use supervised, unsupervised, or semi-supervised learning algorithms to develop sentiment classifiers with labeled or unlabeled textual data. In an article published by Zhang et al., the authors propose a sentence-level classification method for sentiment analysis based on machine learning and CNN. The study demonstrates that CNNs are effective at extracting semantic features from text and attaining high classification accuracy, outperforming conventional machine learning techniques such as SVM and Naive Bayes. The article demonstrates the potential of deep learning techniques in sentiment analysis and their capacity to deal with intricate manifestations of sentiment (Zhang et al., 2015).

2.2.2.2.1 Supervised learning techniques

These methods, including SVM, Naive Bayes, and decision trees, necessitate labeled training data in order to acquire the relationship between input features (e.g., words or phrases) and output labels (e.g., sentiment polarity) (Xhemali et al., 2009).

2.2.2.2.2 Deep learning techniques

CNN and RNN are two cutting-edge techniques that have been effectively used in sentiment analysis to give automated feature extraction and enhanced performance on large-scale datasets (Sadia et al., 2018).

2.2.2.2.3 Unsupervised learning techniques

Without the need for any labeled training examples, techniques like clustering and topic modeling may be utilized to find latent patterns or structures in textual data (Zhang et al., 2015).

2.2.2.2.4 Semi-supervised learning techniques

These methods blend labeled and unlabeled data to boost sentiment classifier performance (Ortigosa-Hernández et al., 2012).

2.2.2.3 Hybrid approaches

These techniques seek to combine the advantages of lexicon-based and machine learning-based techniques, typically through including sentiment lexicons as features in machine learning models or by integrating machine learning classifiers into rule-based systems (Ligthart et al., 2021). In a study, Wang, Xu, and Li propose a hybrid approach to sentiment analysis that incorporates lexicon-based and machine learning-based classification techniques for product reviews. They compute sentiment scores for phrases using a lexicon-based method and then employ an SVM classifier to determine the overall sentiment orientation of the reviews. The hybrid approach outperforms either method alone, demonstrating the potential advantages of integrating various sentiment analysis techniques (Y. Wang et al., 2018).

2.2.3 Sentiment analysis in different languages

2.2.3.1 Challenges in multilingual sentiment analysis

The process of analyzing and extracting opinions, sentiments, and views from textual data written in multiple languages is known as multilingual sentiment analysis. Conducting sentiment analysis in multiple languages presents a number of obstacles (Nankani et al., 2020; Y. Wang et al., 2018):

- *Linguistic variations:* Different languages have distinct syntactic, morphological, and semantic structures, making it difficult to directly employ techniques for sentiment analysis devised for one language to another.
- *Idiomatic expressions:* Identifiable and interpretable idiomatic expressions and vernacular terms that convey emotion can be difficult to identify and translate across languages.
- *Resource availability:* Numerous tools and resources for sentiment analysis, such as sentiment lexicons and labeled training data, are predominantly available for widely spoken languages like English, limiting their applicability for languages with fewer resources.
- *Cultural context:* Different cultures may interpret sentiment differently, necessitating the consideration of cultural nuances when analyzing sentiment in different languages.
- *Ambiguity:* Due to the inherent ambiguity in languages, which can result in numerous interpretations of the same text, sentiment analysis can be challenging. This is particularly true when translating or processing text in multiple languages.

Abovementioned explanations are underlying reasons why this study only focuses on Tweets which are written in English.

2.2.3.2 Cross-lingual sentiment analysis techniques

Cross-lingual sentiment analysis aims to analyze sentiment in one language using resources or models developed for another language. Several techniques have been proposed to address the challenges in cross-lingual sentiment analysis (Sagnika et al., 2020; Xu et al., 2022):

- Machine translation: This approach involves translating the text from the source language to a target language (usually English) and then applying sentiment analysis techniques developed for the target language. However, this method may introduce translation errors and lose sentiment information during the translation process.
- Cross-lingual embeddings: This technique leverages word embeddings, which are vector representations of words, to map words from different languages into a shared semantic space. Cross-lingual embeddings enable the transfer of sentiment analysis models across languages without the need for translation.
- Multilingual models: Some deep learning techniques, such as multilingual BERT (mBERT) and XLM-R, have been pretrained on large multilingual corpora and can be fine-tuned for sentiment analysis tasks across multiple languages.

2.2.4 Sentiment analysis for financial market insights

2.2.4.1 Sentiment analysis for stock market prediction

Sentiment analysis is increasingly used in the financial sector to forecast stock market trends by analyzing investor sentiment derived from a variety of textual data sources, including news articles, financial reports, and social media platforms. The underlying premise is that investor sentiment can impact stock prices by influencing investors' decisions to purchase or sell equities. By capturing and quantifying the collective sentiment, techniques for sentiment analysis can aid in identifying potential market trends and informing investment strategies. Numerous studies have demonstrated that sentiment analysis can offer valuable insights for stock market forecasting, leading to enhanced accuracy when combined with conventional financial indicators (Parry, 2019).

Bollen et al. investigate the relationship among public mood states derived from Twitter data and stock market forecasting (Bollen et al., 2011). They analyze the Granger causality between the emotional dimensions and the Dow Jones Industrial Average (DJIA) using sentiment analysis to quantify the emotions conveyed in a large dataset of tweets. The authors categorize tweets as positive or negative using OpinionFinder, a lexicon-based sentiment analysis tool, and measure mood dimensions using Google-Profile of Mood States (GPOMS). Their findings indicate that specific mood dimensions, such as serenity, show a strong correlation with the DJIA, enabling them to construct a predictive model with an accuracy of 87.6% for predicting the daily up and down fluctuations in the DJIA. Their research demonstrates the potential for applying sentiment analysis on social media data, particularly Twitter, to obtain insights into financial markets and enhance stock market forecasting.

Social media platforms, including Twitter, Facebook, and online forums, have become indispensable information sources for financial market participants, as they offer real-time insights into market sentiment and have the ability to influence investor behavior. Social media data can be analyzed using sentiment analysis techniques to extract and analyze investor sentiment, which may serve as a preceding indicator of market trends or movements. For example, researchers have demonstrated that Twitter sentiment can assist in predicting stock price movements (Reddy et al., 2020) and that sentiment derived from online investor communities can be used to predict stock market volatility (Bukovina, 2016; H. Chen et al., 2013). In the past few years, sentiment analysis of social media data has been applied to cryptocurrency markets, with studies demonstrating a correlation between social media sentiment and cryptocurrency prices (Lamon et al., 2017).

Pano and Kashef (2020) examine the predictive ability of investor sentiment obtained from Twitter data on the cryptocurrency market, concentrating on Bitcoin returns and volatility (Pano & Kashef, 2020). They classify tweets as positive, negative, or neutral using a lexicon-based sentiment analysis approach and the VADER (Valence Aware Dictionary and sEntiment Reasoner) tool. The authors examine the Granger causality between Twitter sentiment scores and Bitcoin returns and volatility. Positive sentiment is found to be positively associated with Bitcoin returns, while unfavorable sentiment is found to be positively associated with Bitcoin volatility. The findings indicate that investor sentiment derived from Twitter data may offer valuable insights into the dynamics of the cryptocurrency market, especially for forecasting short-term fluctuations in Bitcoin prices and volatility.

2.2.4.2 Challenges and limitations in financial sentiment analysis

Regardless of the potential of sentiment analysis for financial market insights, a number of obstacles and constraints must be considered (Birjali et al., 2021):

- *Noise and data quality:* Social media data can be particularly chaotic and unstructured, making it difficult to extract sentiment accurately. In addition, the presence of spam, bots, or irrelevant content can negatively impact the quality of sentiment analysis results.
- *Ambiguity and context:* Financial texts frequently contain domain-specific terminology and intricate concepts, which are difficult for sentiment analysis algorithms to interpret. Moreover, the tone of financial texts can be highly context-dependent, necessitating the use of sophisticated techniques to capture the nuances.
- The financial markets are extremely volatile and sentiment can swiftly change. Therefore, real-time or near-real-time sentiment analysis is essential to effectively capture market sentiment.
- *Causality vs. correlation*: Although numerous studies have reported links between sentiment and financial market movements, it can be difficult to establish a causal relationship between the two.
- *Market efficiency:* According to the efficient market hypothesis, all publicly available content is already reflected in stock prices, making it challenging to consistently achieve above-average returns through sentiment analysis or other predictive techniques.

Regardless of these obstacles, sentiment analysis remains a promising method for gaining financial market insights, as it provides valuable information that can supplement traditional financial indicators and potentially improve investment decision-making processes (Kraaijeveld & De Smedt, 2020). The efficacy of the aforementioned approach is heavily contingent upon the caliber and pertinence of the data that it scrutinizes. Twitter's role becomes significant in this context.

As one of the world's most influential social media platforms, Twitter provides a treasure repository of real-time data comprising diverse perspectives on a vast multitude of topics, including NFTs and other investment products. This abundance of data enables us to leverage the force of public opinion to anticipate market trends and inform financial decisions.

2.3 Twitter as a data source

2.3.1 Data collection from Twitter

2.3.1.1 Twitter API

The REST API and the Streaming API are Twitter's two primary APIs for data acquisition. Both APIs grant developers access to a variety of Twitter data types, including tweets, user profiles, and trends (Xavier & Souza, 2020).

2.3.1.2 REST API

By submitting HTTP requests, the REST API enables developers to query Twitter's database for particular data. It offers access to tweet archives, user profiles, and additional data. Yet, the REST API has rate limits that constrain the number of requests that can be submitted within a given time frame, making it less suited for real-time data collection.

2.3.1.3 Streaming API

In contrast, the Streaming API provides real-time access to Twitter data via an ongoing connection with Twitter's servers. This API allows developers to filter and aggregate tweets according to keywords, user accounts, or geographic locations. The Streaming API is ideally suited for capturing data in real-time, but it does not provide access to messages from the past (Xavier & Souza, 2020).

2.3.1.4 Data extraction using third-party tools

In addition to the Twitter API, there are a number of third-party tools and utilities for data collection, including Tweepy for Python, Twarc for the command line, and NodeXL for Excel. These tools facilitate the extraction of Twitter data by offering pre-built functions and techniques for querying the API and managing authentication.

2.3.1.5 Ethical considerations and data privacy

It is essential to consider ethical implications and data privacy concerns when accumulating Twitter data. Researchers must adhere to Twitter's terms of service and developer guidelines, which define permissible data storage and usage practices. In addition, it is essential to anonymize user data and consider the potential effects of the research on individuals and communities. When publishing study findings, it is standard procedure to aggregate data and prevent presenting information that could potentially identify users or disclose sensitive information (Sohail et al., 2021).

2.3.2 Preprocessing Twitter data

Before analyzing Twitter data, it is necessary to preprocess the text to reduce noise and enhance the efficacy and precision of subsequent analysis techniques (C. C. Aggarwal & Zhai, 2012).

Tokenization: Tokenization is the process of separating the text into individual words, or tokens (Sohail et al., 2021). Owing to the presence of hashtags, mentions, URLs, and other non-standard language constructs, tokenizing tweets can be more difficult than tokenizing regular text. Customized tokenizers, including the TweetTokenizer from the NLTK library (Bird et al., 2009), are capable of handling these Twitter data-specific characteristics.

Stopword Removal: Stopwords are common words with no substantial meaning, such as "a," "an," and "the," that can be eliminated to reduce noise and enhance computational efficiency (Sohail et al., 2021). Customized stopword lists can incorporate Twitter-specific stopwords, such as "RT" for retweets.

Handling URLs, Mentions, and Hashtags: Tweets frequently include URLs, mentions, and hashtags that require preprocessing. To protect user privacy, URLs can be removed or substituted with an interim token, and mentions can be anonymized or removed wholly (C. C. Aggarwal & Zhai, 2012). Hashtags can be separated into individual words to enhance the efficacy of text analysis techniques.

Handling Emoticons and Emojis: Emoticons and emojis communicate emotions and sentiments in tweets and can provide valuable data for sentiment analysis (Kralj Novak et al., 2015). Depending on the analysis objective, these symbols may be substituted with text labels or omitted.

Stemming and Lemmatization: Stemming and lemmatization methods reduce words to their fundamental forms, allowing the consolidation of similar words and enhancing the efficacy of text analysis methods (Sohail et al., 2021). This can be accomplished using specialized stemmers and lemmatizers, including the Snowball stemmer and the WordNet lemmatizer from the NLTK library (Bird et al., 2009).

Preprocessing Twitter data is a critical step in the analysis process, as it helps reduce noise and improve the quality of the data for subsequent sentiment analysis and text classification tasks.

2.3.3 Applications of Twitter data analysis

Analysis of Twitter data has been utilized in a variety of fields to provide valuable insights and help with decision-making processes. In this section, we discuss prevalent applications and provide examples from journal articles.

2.3.3.1 Stock and cryptocurrency market prediction

Twitter sentiment analysis has proven effective for forecasting stock and cryptocurrency market movements. Bollen et al. (2011) showed that public mood states derived from Twitter data can predict stock market changes, whereas Stavroyiannis and Babalos discovered that sentiment analysis of Bitcoin-related tweets can provide insight into short-term price fluctuations and volatility (Bollen et al., 2011; Stavroyiannis & Babalos, 2019).

2.3.3.2 Brand monitoring and reputation management

The analysis of Twitter data can aid businesses in monitoring their brand's reputation and identifying consumer sentiment regarding their products and services. Zhao et al. (2011) suggested a framework for brand monitoring on Twitter that integrates text classification and sentiment analysis techniques to detect and analyze messages related to a brand and evaluate public opinion (Zhao et al., 2011).

2.3.3.3 Political sentiment analysis and election prediction

Utilizing Twitter data analysis, researchers have studied political sentiment and predicted election outcomes. Tumasjan et al. (2010) demonstrated that the volume of tweets referencing political parties could accurately predict election results in Germany, whereas O'Connor et al. (2010) demonstrated that sentiment analysis on tweets could offer insights into public opinion on political issues and candidates (O’Connor et al., 2010; Tumasjan et al., 2010).

2.3.3.4 Public opinion tracking on social issues

Twitter data can also be utilized to monitor public opinion on a variety of social issues, including climate change, health, and crime. Paul and Dredze (2011) investigated public health trends by analyzing tweets containing health-related keywords, whereas Kirilenko and Stepchenkova (2014) utilized sentiment analysis to examine public opinion on climate change by analyzing tweets on the subject (Kirilenko & Stepchenkova, 2014; Paul & Dredze, 2011).

2.3.3.5 Consumer sentiment analysis and product feedback

Businesses and academics can use Twitter data analysis to determine consumer sentiment regarding their products and services, as well as to collect feedback for enhancement. Jansen et al. (2009) examined consumer sentiment on Twitter and discovered that consumers frequently communicate their opinions and experiences with products, providing businesses with valuable information to enhance their offerings and customer service (Jansen et al., 2009).

As it is explored, Twitter data analysis has a wide range of applications and provides valuable insights in a variety of domains. From predicting market trends to gauging public opinion on social issues, this potent tool enables us to identify and comprehend complex patterns within a sea of real-time data. Yet, the research context adds another layer of complication. The NFT market, which is central to this research, operates using blockchain technology. Therefore, it is essential to comprehend the blockchain's underlying concept, its distinct properties, and its critical function in NFT transactions.

In the next section, the foundational principles of this transformative technology will be discussed, enhancing the understanding of the intricacies of the NFT market and the potential influence of Twitter sentiment on its dynamics.

2.4 The concept of the Blockchain

Blockchain technology originally said to be proposed by Nakamoto as the fundamental framework for Bitcoin, is a decentralized, distributed ledger that securely and verifiably records transactions (Nofer et al., 2017). Blockchain technology is distinguished by its transparency, immutability, and security, which are accomplished using cryptographic methods and consensus procedures. In this section elements of blockchain and its use cases have been explored.

2.4.1 Structure and components

Blocks: A blockchain is a series of blocks, each containing a collection of transactions (Nofer et al., 2017). Every block contains a unique identifier called a hash, which is formed by combining the information in the block with the preceding block's hash. This structure assures that any change to the contents of a block invalidates the whole chain, resulting in immutability and tamper resistance (Narayanan & Möser, 2017).

Transactions: Transactions are recordings of data or events that are kept inside blocks. Transactions in cryptocurrencies such as Bitcoin indicate the exchange of digital assets between users (Nakamoto, 2008). The sender digitally signs each transaction, assuring authenticity and non-repudiation.

Consensus Algorithms: Consensus algorithms allow network users to agree on the blockchain's contents, maintaining consistency and deterring double-spending attacks (Bonneau et al., 2015). Proof of Work (PoW) in Bitcoin (Nakamoto, 2008) and Proof of Stake (PoS) in Ethereum 2.0 (Buterin & Griffith, 2017) are two examples of consensus algorithms.

Blockchain technology is supported by a distributed and decentralized network of nodes that are in charge of maintaining and certifying the blockchain (Nofer et al., 2017). When a new block is formed, it is propagated over the network for validation. Before a new block is uploaded to the blockchain, the network's consensus process guarantees that all nodes agree on its validity (Bonneau et al., 2015). This distributed and decentralized architecture enables resistance against attacks since altering the blockchain or disrupting the system would need a majority of nodes to collaborate (Narayanan & Möser, 2017).

Smart contracts are self-executing agreements in which the terms of the agreement are encoded directly into code (Omohundro, 2014). They are a strong feature of blockchain technology, allowing for the automation of complicated transactions and interactions without the need of middlemen. Smart contracts may be used for a variety of reasons, including the creation of bespoke tokens, the management of digital assets, and the automation of corporate operations. Ethereum, a prominent public blockchain platform, pioneered the notion of a Turing-complete virtual computer that enables smart contract execution (Nofer et al., 2017).

Aside from cryptocurrencies and NFTs, blockchain technology has been used in a variety of other industries. Blockchain may increase transparency and traceability in supply chain management by securely documenting the flow of products and commodities along the supply chain (Kshetri & Voas, 2018). Companies such as IBM and Walmart, for example, have worked on a blockchain-based food traceability system that enables efficient monitoring and tracing of items from the farm to the customer (Kamath, 2018).

Blockchain has the potential to transform the way medical records are stored and shared in the healthcare industry, enhancing data security, interoperability, and patient privacy (Ekblaw et al., 2016). Blockchain technology is being used by platforms such as MedRec and MedChain to construct secure, decentralized electronic health record systems that allow patients greater control over their health data and enable data exchange between healthcare practitioners (Azaria et al., 2016; R. Guo et al., 2018).

Blockchain may be utilized in governance to develop transparent and tamper-resistant voting structures, identity management solutions, and public records management (Tapscott & Tapscott, 2016). The "Active Citizen" program in Moscow, for instance, used the Ethereum blockchain to provide a transparent voting platform for people to engage in local decisions (Baudier et al., 2021).

Despite its myriad benefits and prospective uses, blockchain technology is not without its hurdles and restrictions. Scalability is still a challenge, since the growing number of users and transactions on popular blockchain networks such as Bitcoin and Ethereum has resulted in higher transaction fees and slower confirmation times (Nofer et al., 2017). Off-chain transactions, sharding, and layer 2 scaling have been offered as solutions to these scalability issues (Poon & Dryja, 2016; Zamani et al., 2018).

Another issue is the environmental effect of energy-intensive consensus algorithms like PoW, which require large amounts of power to ensure network security (O'Dwyer & Malone, 2014). PoS and Delegated Proof of Stake (DPoS) have been suggested as more energy-efficient consensus procedures (Abreu et al., 2018; Buterin & Griffith, 2017).

2.4.2 Decentralization and security

Blockchain technology is based on decentralization, which means that no central authority controls the network (Nofer et al., 2017). The network is instead managed by a set of nodes, or participants, who verify transactions and keep the blockchain up to current. Decentralization improves network security by requiring a majority of nodes to collaborate in order to modify the blockchain or disrupt the system (Narayanan & Möser, 2017).

2.4.3 Types of Blockchains

There are three major types of blockchain networks: public, private, and consortium (Zheng et al., 2017).

2.4.3.1 Public

Public blockchains, including Bitcoin (Nakamoto, 2008) and Ethereum(Wood, 2014), are accessible to anybody. These networks are distinguished by their resilience to censorship, decentralization, and open-source nature. To protect the network and verify transactions, they depend on consensus methods like PoW and PoS. Public blockchains allow people to freely trade and engage without the need for authorization from a central authority. These networks promote trustlessness by enabling members to depend on cryptographic proofs and consensus methods for security and validation.

2.4.3.1.1 Mining and consensus

Mining is the mechanism through which new transactions are integrated into public blockchains such as Bitcoin, and new currencies are produced as a reward for the miners (Nakamoto, 2008). Miners compete to solve challenging mathematical problems, and the first miner to solve the issue receives the reward and adds the block of transactions to the blockchain (Miers et al., 2013). PoW protects the network by requiring computational effort to produce new blocks, making it expensive and unfeasible for hostile actors to change the blockchain (Eyal & Sirer, 2018).

2.4.3.1.1.1 Decentralized Applications (dApps)

Public blockchains, such as Ethereum, have allowed the creation of dApps, or decentralized apps that operate on a peer-to-peer network (Wood, 2014). Smart contracts are used in these applications to automate processes and interactions, eliminating the need for centralized control or middlemen (Buterin & Griffith, 2017). Decentralized finance (DeFi) platforms, decentralized marketplaces, and decentralized autonomous organizations (DAOs) are examples of dApps (Yue, 2020).

2.4.3.2 Private

Private blockchains are limited networks that are often utilized by businesses for internal procedures (Zheng et al., 2017). Hyperledger Fabric (Androulaki et al., 2018) and Corda (Brown et al., 2016) are two examples of private blockchain systems. These networks provide more control and privacy than public blockchains, but at the expense of decentralization and censorship resistance. Private blockchains are intended for specialized use cases, often inside businesses or groups, where more control, privacy, and efficiency are required (Swan, 2017). These networks are invite-only and provide users with varying degrees of access depending on their positions and responsibilities (Zheng et al., 2017).

2.4.3.2.1 Use cases

Private blockchains have several uses, including supply chain management, interbank transactions, and secure data sharing. Private blockchains help enterprises to expedite processes, decrease expenses, and build confidence among participants by offering a regulated environment (Y. Wang et al., 2019).

2.4.3.2.2 Permissioned nodes

In private blockchains, nodes are permissioned, meaning that they have been granted specific rights to perform certain actions, such as reading data or validating transactions (Zheng et al., 2017). This structure allows for fine-grained access control and ensures that sensitive information is only accessible to authorized participants.

2.4.3.3 Consortium

Consortium blockchains, additionally referred to as federated or permissioned blockchains, are networks that are regulated by a small number of members, including financial institutions or supply chain partners (Zheng et al., 2017). Consortium blockchain systems like Quorum and Ripple are two examples (Swan, 2018). When compared to public blockchains, these networks provide a better mix of decentralization and control, as well as greater privacy and efficiency. Consortium blockchains are hybrid networks that integrate components of both public and private blockchains in order to provide a balance of decentralization and control (Swan, 2017). These networks are administered by a pre-selected set of users who collaborate to maintain the blockchain and make operational choices (Zheng et al., 2017).

2.4.3.3.1 Use cases

Consortium blockchains are ideal for applications in which numerous companies must interact while preserving control over their separate data and procedures. Interbank transactions, supply chain management, and cross-border commerce are some frequent use cases (Tapscott & Tapscott, 2016).

2.4.3.3.2 Governance models

Consortium blockchains use a variety of governance mechanisms, including multi-signature schemes, voting-based systems, or a hybrid of the two (Lazuashvili, 2019). These models guarantee that governing members make choices about the blockchain's functioning jointly, such as adding new participants or upgrading the protocol, (Zheng et al., 2017). Following table summarizes different forms of bockchains as described above:

TABLE 2-1- COMPARISONS AMONG PUBLIC BLOCKCHAIN, CONSORTIUM BLOCKCHAIN AND PRIVATE BLOCKCHAIN (Zheng et al., 2017)

Property	**Public blockchain**	**Private blockchain**	**Consortium blockchain**

Consensus determination	All miners	One organization	Selected set of nodes
Read permission	Public	Could be public or restricted	Could be public or restricted
Immutability	Nearly impossible to tamper	Could be tampered	Could be tampered
Efficiency	Low	High	High
Centralized	No	Partial	Partial
Consensus process	Permissionless	Permissioned	Permissioned

2.4.4 Cryptocurrencies

Cryptocurrencies are digital or virtual currencies that rely on cryptographic methods to conduct safe and decentralized transactions (Narayanan & Möser, 2017). Bitcoin, the most well-known cryptocurrency, was created by Nakamoto (2008) as a peer-to-peer electronic cash system. Ethereum and Litecoin are two more prominent cryptocurrencies (S. Aggarwal & Kumar, 2021).

2.4.4.1 Key features

Cryptocurrencies share numerous fundamental characteristics, including decentralization, anonymity, and limited supply. Decentralization guarantees that no authority controls the network, preventing censorship and reducing the possibility of single points of failure (Nofer et al., 2017). Anonymity is accomplished via the use of public and private keys, which enable users to perform transactions without disclosing their true identities (Narayanan & Möser, 2017). Many cryptocurrencies, such as Bitcoin, have a restricted supply, which may help preserve their value over time (Nakamoto, 2008).

2.4.4.2 Applications and use cases

Digital Payments: Cryptocurrencies may be used as a means of exchange for goods and services, allowing for quick, safe, and low-cost transactions without the need for third-party intermediaries like banks (Nakamoto, 2008). Bitcoin and other cryptocurrencies are accepted as payment by companies such as Microsoft, Overstock, and Newegg (Kaplanov, 2012).

Remittances: When compared to conventional ways, cryptocurrency may simplify cross-border transfers by lowering transaction costs and boosting speed. Companies such as BitPesa and Abra provide cryptocurrency-based remittance services (Rella, 2019).

Decentralized Finance: DeFi is a burgeoning industry that uses blockchain technology and cryptocurrencies to offer financial services including lending, borrowing, and asset management without the need of middlemen (Meyer et al., 2022). DeFi services are provided through platforms such as MakerDAO, Compound, and Uniswap, which are based on the Ethereum network (Buterin & Griffith, 2017).

Store of Value: Some cryptocurrencies, particularly Bitcoin, are often considered a store of value and a hedge against traditional financial markets' volatility. The digital scarcity and decentralized nature of cryptocurrencies make them attractive as alternative investments during times of economic uncertainty (Baur, Dimpfl, et al., 2018; Baur, Hong, et al., 2018).

Initial Coin Offerings (ICOs) and Token Sales: ICOs and token sales are methods of generating cash in which firms and projects issue their own tokens or cryptocurrencies. Adhami et al. (2018) state that these tokens often reflect a stake in the project or offer usefulness inside the ecosystem (Adhami et al., 2018). ICOs gained popularity in 2017 and have subsequently faced greater regulatory attention in a number of countries.

Stablecoins: Stablecoins are cryptocurrencies that are intended to have a consistent value and are often tied to a fiat currency or a basket of assets. They want to combine the stability of conventional currencies with the advantages of cryptocurrencies, such as rapid transactions and borderless payments. Tether (USDT), USD Coin (USDC), and DAI are examples of stablecoins (Fiedler & Ante, 2023; Ohk et al., 2021).

Non-Fungible Tokens: NFTs are one-of-a-kind digital assets that indicate ownership or evidence of authenticity for a variety of goods, including art, collectibles, and virtual real estate (Q. Wang et al., 2021). NFTs, which are based on blockchain technology, allow for the decentralized generation, trading, and monetization of digital content while maintaining provenance and scarcity (Herian et al., 2021). NFTs are the main objective of this study which are going to be explored further in this study.

As the bitcoin ecosystem evolves, we should expect to witness new use cases and applications emerge, proving the technology's adaptability and promise. Furthermore, as legal frameworks around cryptocurrencies evolve, the integration of cryptocurrencies into mainstream banking and commerce is anticipated to rise, bringing up new possibilities for both firms and consumers (Juels et al., 2016).

2.4.5 Non-Fungible Tokens

NFTs are indivisible, one-of-a-kind digital tokens that reflect ownership of a digital or physical asset (Q. Wang et al., 2021). NFTs, unlike cryptocurrencies, cannot be exchanged one-for-one since each token has a distinct value and set of attributes.

2.4.5.1 NFT standards and platforms

ERC-721: ERC-721 is the Ethereum network's first widely recognized standard for establishing and maintaining NFTs (“Ethereum Improv. Propos.,” 2023). The ERC-721 standard is used by platforms like as CryptoKitties, a digital collectibles game, to produce unique, transferable digital assets (Q. Wang et al., 2021).

FIGURE 2-2- ASSORTMENT OF CRYPTOKITTIES NFT COLLECTION (CryptoKitties, 2023)

ERC-1155: ERC-1155 is a more sophisticated NFT standard that permits the production of fungible and non-fungible tokens inside the same smart contract. This standard allows for more efficient and flexible token handling, making it appropriate for applications like as gaming and digital art platforms (Q. Wang et al., 2021).

Flow Blockchain: Flow is a blockchain developed primarily for high-performance applications like as NFTs, gaming, and dApps (Q. Wang et al., 2021). Flow, created by the same team that created CryptoKitties, attempts to solve the Ethereum network's scalability difficulties via the use of a multi-node architecture and resource-oriented programming approach (Pelechrinis et al., 2022). NBA Top Shot, a digital collectibles site for basketball enthusiasts, and VIV3, a worldwide NFT marketplace, are two notable initiatives based on Flow.

Tezos NFT Standards: Tezos, another smart contract platform, has developed its own NFT standards, including FA2 and TZIP-12 (Bamakan et al., 2021). These specifications enable developers to construct, manage, and trade NFTs on the Tezos network, which has cheaper transaction costs and a more energy-efficient consensus process than Ethereum (Harz & Knottenbelt, 2018). Tezos NFT standards are used by platforms like as Hic et Nunc and Kalamint to market digital art and collectibles.

Binance Smart Chain (BSC): Binance Smart Chain is a platform for smart contracts created by Binance, one of the leading cryptocurrency exchanges. Due to its consensus process and network design, BSC is compatible with Ethereum-based NFT standards like as ERC-721 and ERC-1155, and it allows quicker and cheaper transactions. Projects such as BakerySwap and Treasureland use BSC to manufacture and exchange NFTs at a lower cost (Academy, 2022).

2.4.5.2 Applications and use cases

NFTs have enabled a diverse set of applications and use cases, indicating their potential to transform a variety of industries and sectors. Among the major applications and use cases for NFTs are:

Digital Art: NFTs have gotten a lot of interest in the digital art world because they allow artists to make, sell, and exchange one-of-a-kind digital artworks with provable ownership and provenance (Herian et al., 2021). Artists may tokenize and monetize their masterpieces using NFT markets like as OpenSea, Rarible, and SuperRare, while collectors can buy, exhibit, and resell these artworks in a decentralized way (Q. Wang et al., 2021).

Collectibles and Gaming: NFTs have found broad application in digital collectibles and gaming, where they may be used to represent in-game objects, characters, or virtual products (Böhme et al., 2015). CryptoKitties, a popular blockchain-based game, allowing users to acquire, breed, and trade one-of-a-kind digital cats represented by NFTs (Q. Wang et al., 2021). Other initiatives, such as Decentraland and The Sandbox, leverage NFTs to enable users to construct, explore, and commercialize virtual environments (Sharma et al., 2022).

Sports Memorabilia: NFTs may be used to tokenize and exchange digital sports memorabilia like as video highlights, player cards, or signatures (Chohan, 2021). NBA Top Shot, constructed on the Flow blockchain, provides officially authorized NBA memorabilia in the form of NFTs, enabling fans to own and exchange unique basketball game moments (Q. Wang et al., 2021).

Music & Entertainment: NFTs may be used to represent digital music, movies, or other types of creative output, enabling artists to tokenize, sell, and distribute their products in a decentralized and transparent way (Johnson & are NFT, 2022). Platforms like as Audius and Catalog use NFTs for music streaming and distribution, providing new income streams for artists as well as unique experiences for fans.

Domain Names and Virtual Real Estate: NFTs may also represent digital assets like as domain names and virtual real estate (Herian et al., 2021). NFTs are used by projects like ENS (Ethereum Name Service) to administer decentralized domain names, while platforms such as Decentraland and Cryptovoxels employ NFTs to enable users to purchase, trade, and construct virtual properties (Sharma et al., 2022).

Intellectual Property and Licensing: NFTs have the potential to be utilized for overseeing intellectual property rights and licensing since they offer a transparent, tamper-proof, and readily transportable system for monitoring ownership and consumption of creative works (Q. Wang et al., 2021). This may assist artists in better protecting their rights and monetizing their inventions (Herian et al., 2021).

Understanding the nature and uses of NFTs, particularly with a diversity of standards and platforms, is crucial to our research. These digital tokens, which represent a new era of digital ownership, have emerged as key players in a variety of sectors, spanning to digital art, gaming, sports, music, electronic real estate, and intellectual property rights. The digital art market stands out as particularly relevant in our context. The use of NFTs in this sphere has provided artists with unprecedented opportunities to create, monetize, and distribute their work. NFT artwork, which is frequently bought, sold, and traded on platforms such as OpenSea and Rarible, has gained enormous popularity and captured the world's attention.

Therefore, the interaction of social sentiment and the NFT art market becomes a central focus of our study. The market's dynamic and distinctive qualities may magnify or affect the effect of public mood on NFT pricing. In our next section, we will investigate the "NFT Artwork Market" and its mechanics and trends, expanding our understanding of the context in which Twitter sentiment operates.

2.5 NFT artwork market

2.5.1 Growth and trends in the NFT art market

In recent years, the NFT art industry has grown significantly, with total sales exceeding $2 billion in the first quarter of 2021 alone (Sharma et al., 2022). This growth in interest may be ascribed to a number of causes, including greater digitalization of the art industry, the advent of crypto-currencies, and a desire for digital ownership and provenance (Herian et al., 2021). The sale of digital artist Beeple's NFT artwork "Everydays: The First 5000 Days" (Figure 2-3) for $69.3 million in March 2021 represented a watershed moment in the general recognition of NFTs as a valid art form (Q. Wang et al., 2021).

FIGURE 2-3- EVERYDAYS — THE FIRST 5000 DAYS

According to a recent analysis by Grand View Research, Inc., the global non-fungible token market is expected to reach USD 211.72 billion by 2030, with a compound annual growth rate (CAGR) of 34.2% from 2023 to 2030. The rising worldwide demand for digital art is one of the key causes driving the rise of the NFT sector. Digital art is artwork that is shown or created utilizing digital technologies (Grand View Research, 2023).

2.5.2 Factors driving the popularity of NFT artwork

Several reasons have aided NFTs' appeal in the art industry. One significant driver is the capacity to authenticate ownership and authenticity of digital artworks via blockchain technology, which enables artists and collectors to validate an artwork's history and uniqueness (Q. Wang et al., 2021). Another issue is the greater accessibility of the art market through NFTs, which allows artists to avoid conventional gatekeepers like galleries and auction houses and interact directly with buyers and collectors (Q. Wang et al., 2021).

Furthermore, NFTs have opened up new avenues for artists to commercialize their work and earn royalties via secondary sales, providing a more sustainable business model for creators (Herian et al., 2021). Furthermore, the development of cryptocurrencies and the growing popularity of blockchain technology has aided in the acceptance of NFTs in the art market, since they offer a decentralized and secure platform for generating, trading, and storing digital assets (Sharma et al., 2022).

2.5.3 Key platforms and marketplaces for NFT art

To support the creation , selling, and exchange of digital art, many NFT markets and platforms have evolved. These include OpenSea, Rarible, and SuperRare, which enable artists to mint, list, and sell their NFT artworks while allowing collectors to explore, buy, and resell these one-of-a-kind items (Q. Wang et al., 2021). Other platforms, such as Foundation and Async Art, specialize on certain niches of the NFT art industry, such as curated choices of high-quality artwork or programmable art that changes over time depending on specified parameters (*Async: Create Art and Music NFTs*, 2023).

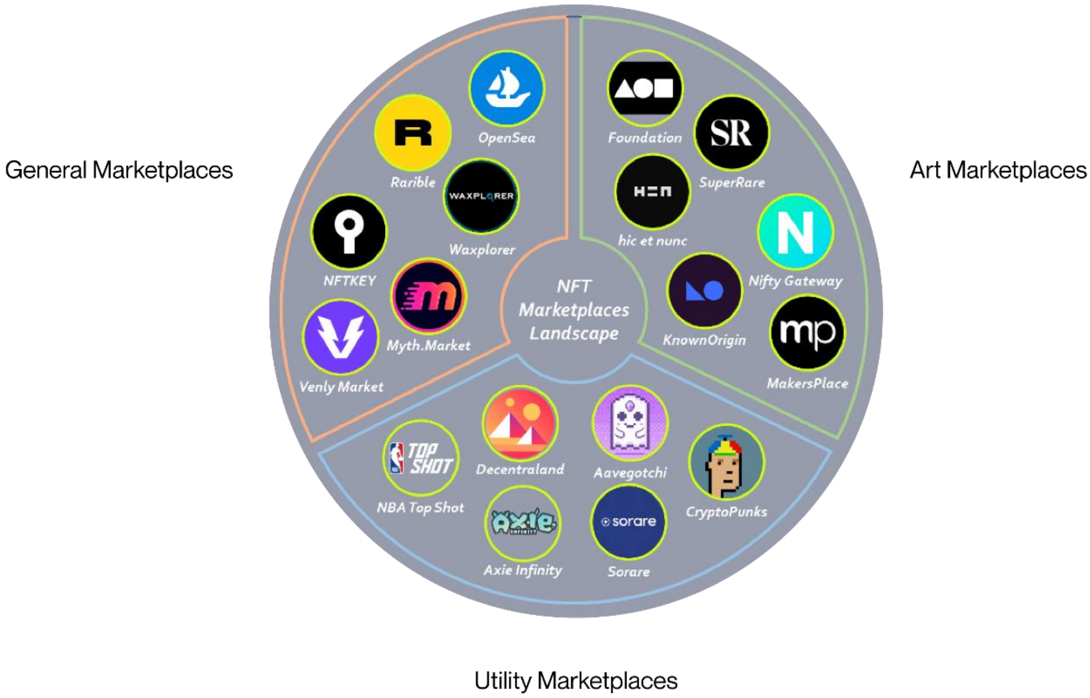

FIGURE 2-4- NFTS' MARKETPLACE SEGMENTATION (Tech, 2023)

2.5.4 Creation and tokenization of NFT artworks

2.5.4.1 Creating digital art for NFTs

Depending on the artist's chosen medium and style, digital art for NFTs may be generated using a variety of tools and software, including Adobe Creative Suite, Blender, or Procreate (Herian et al., 2021). Artists may create a variety of digital artworks, including 2D photographs, 3D models, animations, and interactive pieces, which are subsequently tokenized as NFTs and sold in the market (Q. Wang et al., 2021).

2.5.4.2 Tokenization process and standards

Tokenization entails creating a one-of-a-kind digital token on a blockchain network to represent the digital artwork (Herian et al., 2021). This procedure often entails the use of a particular NFT standard, such as ERC-721 or ERC-1155, which describe the token's attributes and functionalities. These standards guarantee that the NFT is interoperable with other platforms, wallets, and marketplaces, enabling frictionless trade and ownership transfer (Q. Wang et al., 2021).

2.5.4.3 Minting and listing NFT artworks on marketplaces

After developing a digital artwork and selecting an acceptable NFT standard, an artist may mint the NFT, which includes establishing a unique, non-fungible token to represent the artwork on the blockchain (Herian et al., 2021). Typically, minting entails uploading the artwork to a decentralized storage system, including the InterPlanetary File System (IPFS), which assures that the artwork stays available even if the original creator's server goes down (Q. Wang et al., 2021).

After minting the NFT, the artist may offer it on NFT markets like OpenSea, Rarible, or SuperRare, where prospective customers can examine and purchase the artwork (Herian et al., 2021). Setting a price or auction criteria, as well as giving information, such as a title, description, and tags, to assist prospective purchasers identify and understand the artwork, is often involved in listing an NFT (Q. Wang et al., 2021).

2.5.5 Buying and selling NFT artworks

2.5.5.1 NFT valuation

Because of their uniqueness and newness, valuing NFTs is difficult. NFT value is determined by elements such as owner and buyer perceptions, scarcity, access, and distribution methods. Valuation may vary for creators, buyers, and owners, and can be very speculative until an NFT is sold. Traditional valuation measures are not applicable to NFTs, making it impossible to estimate their value. For example, there is presently no particular advice in US GAAP (Generally Accepted Accounting Principles) on how to account for NFTs, and they do not fulfill the GAAP definitions of cash, marketable securities, financial instruments, or inventories (Regner et al., 2019). Cryptocurrencies are often classified as intangible assets, although the volatility and speculative nature of digital assets make this definition difficult. Impairment accounting is especially challenging for NFTs owing to difficulties in determining fair values. Risk factors such as transaction security and internal controls may also influence value. Companies and auditors may have difficulty validating the existence and ownership of NFTs and may need to depend on IT professionals to corroborate these data. However, there have been several efforts to provide a framework for such values (Ali et al., 2023; Jain et al., 2022; Kaczynski & Kominers, 2021).

Kaczynski and Kominers identify seven characteristics to examine when establishing the value of an NFT, which include chain security, on-chain or off-chain information, age, creator and community, scarcity, release rate, and richness (Kaczynski & Kominers, 2021). It also analyzes the contemporary tendency of destroying original works in order to boost the value of the accompanying NFT, giving the NFT the distinction of being the “only remaining form” of the artwork. However, the article indicates that authors might use contractual limits as an alternative to destruction, such as limiting the exhibition of the original work or transferring copyright to the buyer. Contractual constraints may assist in improving the value of an NFT, but neither destruction nor contractual limits can prohibit others from seeing, downloading, sharing, or duplicating the picture linked with the NFT online.

According to Kaczynski and Kominers (2021), in order to flourish, NFT initiatives must make significant use of the technology, harness a community of users, sustain continuous engagement, offer accessible on-ramps for new users, and weather crypto market volatility. The future of NFTs is unknown, but their capacity to allow new markets and produce value via community participation hints to their potential significance.

Dowling also investigates if NFT price is linked to cryptocurrency pricing (Dowling, 2022). A spillover score reveals relatively little volatility transmission effects between cryptocurrencies and NFTs. However, wavelet coherence analysis reveals co-movement between the two sets of markets. This shows that bitcoin price behaviors may be useful in understanding NFT pricing trends.

However, the low volatility transmissions suggest that NFTs may be regarded as a low-correlation asset class separate from cryptocurrencies.

From another angle, Dave Beech differentiates between the price and value of an artwork, with price being the money it may be traded for in the market and value being the entire labor-time devoted in discussing, watching, and recreating it (Russell, 2022). Beech provides a Marxist view of aesthetic worth, stressing work time in the building of creative notoriety. The high cost of art is due to its high standing within the art world, which is pushed by non-purchasing customers such as scholars, pundits, and fellow artists. Beech's approach departs from the traditional Marxist labor theory of value in that it focuses on consumer work rather than production labor. The more the labor time of non-purchasing art consumers, the higher the worth of the artwork. Beech's framework enables us to comprehend how prices arise without exaggerated prediction abilities (Russell, 2022).

Artistic discourse differs from marketing in that it is unaffected by commercial concerns. The "aura" of an artwork is formed by the distance between creative discourse and those who stand to profit financially from its value inflation. The decentralization of art discourse adds to the ambiguity and disorganized nature of reputational changes, which makes some works seem miraculous. To maintain a high price over time, a continual process of enrichment via fresh dialogues about artworks is required, in addition to the novelty of their unusual price tags (Kwon & Tae, 2022).

Recent quantitative studies on the NFT market have focused on measurable components of value and reputation, while Dave Beech's study advises incorporating harder-to-quantify characteristics. The long-term worth of an artwork, whether tied to an NFT or not, is determined by its potential to be enhanced in a manner that looks independent of those who monetarily profit from its increasing value. NFTs such as CryptoPunks are valued because they are regarded as "blockchain antiques" with a long history (Dylan-Ennis et al., 2023). Instead of concentrating on the medium, it may be more useful to study the institutions that sustain and distribute the reputational discourses that determine creative worth.

Although NFTs seem to be a means to liberate digital artists from the difficulties associated with simple duplication, their reputational worth is still dependent on replication, circulation, remark, and debate. The problem for the crypto world is to create long-term discursive work to enhance the worth of NFTs, or the art world's "gatekeeping" institutions (Clayman & Reisner, 1998) may need to be invoked to sustain the NFT market.

2.5.5.2 Bidding and purchasing process

NFT artworks are often purchased and sold via auctions or fixed-price transactions on marketplaces such as OpenSea (Herian et al., 2021). Buyers may explore available artworks and put bids or buy them outright, depending on the artist's preferred sale method (Q. Wang et al., 2021). When a buyer successfully purchases an NFT artwork, ownership of the token is transferred to their digital wallet and the transaction is recorded on the blockchain, giving a permanent record of provenance (Herian et al., 2021).

2.5.5.3 Payment methods and cryptocurrencies

Payment for NFT artwork is often paid using cryptocurrencies such as Ether (ETH) for artworks generated on the Ethereum network or other platform-specific tokens such as Flow for artworks created on the Flow blockchain (Herian et al., 2021). The adoption of cryptocurrency allows for quick, safe, and transparent transactions, as well as a decentralized and worldwide payment system that may avoid conventional financial intermediaries (Q. Wang et al., 2021). Some markets allow payment in fiat currencies like US dollars, while on other platforms, cash or credit cards cannot be used to pay for an NFT directly. Prices are often established in the cryptocurrency that is utilized by the network where the NFTs are registered. If a creator creates an NFT on the Ethereum blockchain, for example, it must be paid for using Ether (ETH), the Ethereum network's native coin. If the blockchain is Solana, the native token on the Solana network is Solana (SOL).

2.5.5.4 Secondary market trading and royalties

Secondary markets exist for NFT artworks, enabling collectors to sell and profit from their digital assets (Herian et al., 2021). Many NFT platforms and standards encourage the development of royalty systems, which allow artists to get a portion of sales income when their artwork is resold on the secondary market (Q. Wang et al., 2021). This offers producers with a more consistent revenue stream while also motivating them to continue creating high-quality and valued artwork (Herian et al., 2021).

2.5.6 Displaying and storing NFT artworks

2.5.6.1 Digital galleries and virtual exhibitions

NFT artworks may be shown in a variety of digital settings, including web-based exhibitions, virtual reality venues, and augmented reality apps (Herian et al., 2021). Platforms such as Cryptovoxels, Decentraland, and Somnium Space let users to construct and personalize virtual environments in which to display their NFT art collections, organize virtual exhibits, and even attend live events and performances (Q. Wang et al., 2021).

2.5.6.2 Decentralized storage solutions

The actual digital data connected with NFT artworks are often saved on decentralized storage systems like as IPFS (InterPlanetary File System), ensuring that the artwork remains accessible and safe even if the original creator's site goes down (Herian et al., 2021). IPFS is a content-addressed, distributed storage system that enables users to access and exchange files across several nodes, hence boosting the stability and availability of digital artworks (Q. Wang et al., 2021).

2.5.6.3 Security and ownership verification

The blockchain technology that underpins NFT artworks offers a safe and transparent means for validating digital art ownership and provenance (Herian et al., 2021). Each NFT is linked to a unique token on the blockchain, which holds details about the artwork, such as the artist, date of production, and ownership history. This information is irreversible and transparent, making forging or altering the provenance of an NFT artwork very difficult (Q. Wang et al., 2021).

Aside from blockchain-based provenance records, NFT owners may safeguard their digital assets using digital wallets, which contain the private keys required to access and control their NFTs (Herian et al., 2021). These wallets may be software-based or hardware-based, with the latter adding an extra layer of protection through physical devices that keep private keys offline, minimizing the danger of hacking or theft (Q. Wang et al., 2021).

2.5.7 Challenges and criticisms of the NFT art market

2.5.7.1 Environmental concerns

The environmental effect of blockchain networks, especially those that depend on energy-intensive consensus algorithms like PoW utilized in the Ethereum network, is one of the key concerns of the NFT art market (Herian et al., 2021). The minting, purchasing, and selling of NFTs may use considerable quantities of power, adding to greenhouse gas emissions and raising worries about the market's sustainability (Q. Wang et al., 2021). To address these problems, several artists and platforms are investigating alternate, more energy-efficient blockchain networks or consensus algorithms, such as PoS (Herian et al., 2021).

2.5.7.2 Intellectual property and copyright issues

The NFT art market has also prompted concerns about intellectual property and copyright, since digital artworks may be readily duplicated and replicated, possibly resulting in unlawful use or plagiarism (Herian et al., 2021). While NFTs may give evidence of ownership and provenance, they do not prevent illicit copying or dissemination of the underlying digital goods (Q. Wang et al., 2021). Artists and collectors must be careful in preserving their intellectual property rights and prosecuting copyright claims, while platforms and marketplaces may need to develop more effective anti-infringement procedures (Herian et al., 2021).

2.5.7.3 Market volatility and speculation

Concerns regarding market volatility and speculative behavior have arisen as a result of the quick development and high-profile sales of NFT artworks, since some investors may want to benefit from short-term price swings rather than investing in the long-term worth of the artwork (Q. Wang et al., 2021). This speculative market may lead to price bubbles and subsequent collapses, undermining the NFT art market's legitimacy and stability (Herian et al., 2021). When engaging in the NFT art market, artists, collectors, and investors must exercise prudence and due diligence to prevent possible hazards and maintain the industry's long-term survival (Q. Wang et al., 2021).

2.5.8 Future prospects and developments in the NFT art market

2.5.8.1 Innovations in NFT standards and platforms

As the NFT art industry expands, there will most certainly be continual innovation in the creation of NFT standards and platforms. These developments may make the design, trading, and administration of NFTs more efficient, safe, and user-friendly, hence increasing acceptance and market growth (Q. Wang et al., 2021). Emerging NFT standards, for example, may include features such as fractional ownership, royalties, and enhanced metadata processing, giving artists and collectors more freedom and control over their digital assets (Herian et al., 2021). Furthermore, new platforms that cater to specialized niches within the art market, delivering personalized services and features that answer the distinct demands and tastes of diverse artist and collector groups, may arise (Q. Wang et al., 2021).

2.5.8.2 Integration with traditional art markets

By linking the physical and digital domains, the NFT art market has the potential to disrupt the conventional art industry (Q. Wang et al., 2021). As more conventional artists and institutions investigate the possibilities of NFTs, prospects for cooperation and integration between the two markets may rise (Herian et al., 2021). Some artists, for example, have started to experiment with embedding NFTs into their physical artworks or providing NFTs as a way of authentication for limited edition prints (Q. Wang et al., 2021). Furthermore, auction houses like Christie's and Sotheby's have begun to embrace NFTs, staging high-profile digital art auctions and reflecting a rising acceptance of NFTs inside the conventional art industry (Joy et al., 2022)(Herian et al., 2021). As the borders between the digital and physical art industries continue to blur, new business models, alliances, and possibilities are expected to emerge, altering the art world even more.

2.5.8.3 New use cases and applications for NFTs in the art world

As the NFT art business grows, new use cases and applications for NFTs in the art world are projected to emerge, fueling additional innovation and development (Q. Wang et al., 2021). NFTs, for example, might be used to enable decentralized curation and presentation of digital art, letting artists and collectors to display their works in virtual galleries or mixed-reality spaces without the need for centralized middlemen (Ahmet, n.d.). Furthermore, NFTs may play a role in improving provenance tracking and copyright management for both digital and physical artworks, allowing for a more transparent and safe method of establishing ownership and history (Q. Wang et al., 2021). As artists, collectors, and institutions continue to experiment with NFTs and investigate their possible uses, the NFT art market is expected to change and expand, creating new possibilities and chances for creativity and innovation in the art world.

2.5.8.4 Promoting sustainability

NFTs have the potential to enhance sustainability across several industries. NFTs may develop transparent, secure, and decentralized platforms that encourage sustainable behaviors by employing blockchain technology.

Sustainable supply chains: NFTs may be used to monitor and verify the sustainability of items throughout their supply chain. NFTs may assure transparency, traceability, and authenticity throughout the process by tokenizing goods or their components (Wu et al., 2023). This may support ethical sourcing, waste reduction, and sustainable business practices.

Environmental conservation: By tokenizing natural resources, ecosystems, or species, NFTs may aid conservation efforts. Tokenizing endangered species or their ecosystems, for example, might provide incentives for conservation and restoration initiatives (Dumitriu et al., 2021). Carbon credits may also be tokenized using NFTs, creating a transparent and efficient platform for trading and verifying emissions reductions (W. Guo, 2022).

Sustainable fundraising: NFTs may be used to collect funding for long-term projects or initiatives. Organizations may generate unique and valuable commodities to sell or auction for fundraising reasons by tokenizing digital art or other digital assets. Artists and non-profit groups have previously adopted this strategy to assist environmental concerns (Ertürk et al., 2021).

Circular economy: NFTs may help to build a circular economy by allowing decentralized and transparent systems for resource recycling, reuse, and sharing. Tokenizing resources, goods, or services may help in resource allocation and waste reduction.

Afterwards, by allowing transparent, decentralized networks that encourage ethical activities, environmental conservation, sustainable fundraising, and circular economies, NFTs have the potential to promote sustainability across several sectors. However, addressing the environmental effect of NFTs and blockchain technology itself is critical to ensuring that these breakthroughs are really sustainable.

Understanding and properly projecting NFT pricing is crucial, given the dynamic nature of NFT standards, their connection with existing markets, and the expanding use cases. Artists, collectors, and institutions need knowledge of market dynamics for informed judgments on NFT production, acquisition, or sale. Predicting NFT pricing effectively has substantial ramifications, including enhancing financial planning and investment strategies, and stimulating innovation by providing fair returns. Moreover, grasping elements impacting these pricing aids in the transparency of this developing market, extending its reach to more players.

The next section concentrates on the empirical examination of NFT artwork price prediction. We explore current research on sentiment analysis and its impact on the NFT art market. Bridging theory and reality, we employ modern data science tools to analyze market behavior. This research provides unique insights into the complexity of the NFT art market via sentiment analysis and price prediction.

2.6 Recent works on the sentiment analysis and NFT artwork price prediction

2.6.1 Prediction and predictors of NFT prices

Due to the recent emergence of NFTs, limited research has been conducted on them. The majority of research has examined the relationship between blockchain, cryptocurrencies, and NFTs, focusing on protocols, standards, security, and obstacles. Some studies investigate the relationship between NFT markets and conventional crypto assets such as Ethereum and Bitcoin, while others focus on the sub-markets of NFTs where millions of dollars are transacted daily.

This study focuses on the underdeveloped field of NFT asset valuation, which has received scant attention. Recent research by Nadini et al. used machine learning algorithms to construct a predictive model based on sales history and visual characteristics, but excluded social media characteristics (Nadini et al., 2021). In addition, Kapoor et al. intended to determine the influence of OpenSea and social media features on the valuation of NFT assets (Kapoor et al., 2022). Their findings indicate that social media features increase accuracy by 6% compared to models that use only NFT platform features as a baseline. Important social media features include the number of user membership lists, favorites, and retweets.

Meyns et al. utilized topic modelling as a data analysis technique to comprehend NFT-related concerns on Twitter (Meyns, 2022). Concerns about attacks and threats from third parties and trading and the function of marketplaces are two of the 19 overarching concerns expressed on Twitter regarding NFTs.

Furthermore, Pinto-Gutiérrez et al. analyzed the factors fueling interest in NFTs between 2017 and 2021 using Google search queries (Pinto-Gutiérrez et al., 2022). The study demonstrates a positive correlation between Google searches for "non-fungible token," "NFT," and specific NFT collections such as "Cryptopunk" and "Decentraland" and significant cryptocurrency returns. Using vector autoregressive (VAR) models, the researchers discovered that Bitcoin returns from the previous week have a significant impact on interest in NFTs. Wavelet coherence analysis also revealed that investors are more interested in NFTs after Bitcoin and Ether return increases.

There are more studies that have investigated the correlation between social media sentiment and the prices of cryptocurrencies. Sattarov et al. examined the relationship between Bitcoin price fluctuations and Twitter sentiment and discovered a significant correlation between the two variables (Sattarov et al., 2020). While their study does not explicitly address the prices of NFT artwork, it illustrates the potential applicability of sentiment analysis techniques to digital assets.

Giudici et al. examined the predictive potential of Twitter sentiment for the prices of different cryptocurrencies (Giudici & Abu-Hashish, 2019). The relationship between sentiment and price variations was analyzed using a combination of machine learning techniques and Granger causality tests. Their findings suggested that sentiment analysis could provide insightful information about the behavior of cryptocurrency markets.

2.6.2 Future Directions for Research in Sentiment Analysis and NFT Price Prediction

Existing literature has predominantly concentrated on cryptocurrencies, but future research may investigate the application of sentiment analysis techniques to the NFT art market. Researchers may investigate the connection between social media sentiment and NFT artwork prices, in addition to the impact of influencer endorsements and online community activity on price fluctuations.

In addition, the development of novel methodological approaches and the incorporation of multi-modal data, such as visual characteristics of NFT artwork, could contribute to a deeper comprehension of the factors that influence the prices of NFT artwork. As the field continues to expand, there will likely be a growing interest in the application of sentiment analysis techniques to the NFT art market, which will be the objective of this study and can provide artists, collectors, and investors with valuable insights.

2.7 Conclusion

This literature review examined the applications of sentiment analysis in various domains, with an emphasis on its potential for predicting the prices of NFT artworks. The history, methods, and languages employed in sentiment analysis, as well as the use of social media platforms such as Twitter for data acquisition and preprocessing were discussed. The review also addressed blockchain technology, cryptocurrencies, and the emergence of non-fungible tokens on the art market.

The potential applications of sentiment analysis in the NFT artwork market were discussed, including its use in price prediction by analyzing public opinions and emotions expressed on social media platforms, online art communities, forums, and news media. Despite the challenges and limitations of sentiment analysis, such as the subjective nature of art and the quickly evolving NFT market, the technique has the potential to provide artists, collectors, and investors with valuable insights for traversing the complex world of NFT art.

Future research could develop more accurate and robust predictive models for NFT artwork prices by integrating sentiment analysis with other data sources and market factors, thereby augmenting our comprehension of this emerging market's dynamics.

3 METHODOLOGY

3.1 Introduction

The technique used in the research, which focuses on understanding the function of feelings in the NFT market, is presented in this chapter. The study approach consists of a systematic procedure that begins with keyword selection and progresses to the extraction and analysis of social media material and financial data on NFTs. The keyword selection procedure strives to give a thorough representation of the NFT market by emphasizing relevance, frequency, specificity, adaptability, and comprehensiveness. Twitter is mostly used for data extraction, with an academic-level API used to collect a large number of data. Sentiment analysis, a critical component of the research, uses a well-established vocabulary to detect and classify sentiments in the obtained data. Financial data on NFTs is gathered from numerous platforms in addition to social media material, offering crucial insights into NFT market patterns and pricing. The last section of this chapter will concentrate on data analysis, with the goal of better understanding the influence of sentiment on the NFT market.

3.2 Keywords selection

In the framework of the NFT market, keywords are the foundation for precisely assessing the sentiments conveyed in social media content. By selecting keywords with care, researchers can make certain that the sentiment analysis concentrates on pertinent discussions and opinions regarding NFTs, their pricing, and the variables affecting their value. Proper keyword selection enables a more focused and meaningful examination of social media interactions by eliminating noise from unrelated conversations (Medagoda & Shanmuganathan, 2015).

3.2.1 Criteria for keyword selection

The following criteria have been considered while choosing relevant keywords for this study:

- Relevance to the NFT market: Keywords ought to be explicitly associated with non-fungible tokens, prominent NFT platforms, particular NFT collections, or prominent NFT artists and creators.
- Frequency of use: To ensure that a substantial quantity of data is available for analysis, the selected keywords ought to be utilized frequently by the NFT community.
- Specificity: Keywords ought to be sufficiently specific to encompass pertinent discussions without being excessively restrictive, which could limit the scope of the investigation.
- Flexibility: The keyword list must be adjustable in order to cover growing trends, new platforms, or noteworthy events in the NFT market that may influence sentiment and price.
- Comprehensiveness: The chosen keywords ought to offer a well-rounded depiction of the NFT market, including discussions regarding pricing, art, collectibles, digital goods, and investment opportunities, among other topics.

3.2.1.1 Generic Keywords

The following table demonstrates the „generic keywords" used for data collection. These keywords aim to capture an overall picture of the crypto market. Considering earlier works (Ante, 2022; Dowling, 2022), it is shown that change in the whole landscape can impact NFT valuation. Looking at the bigger picture would aid the research in considering the overarching impact of the market as well.

TABLE 3-1 – GENERIC KEYWORDS AND JUSTIFICATION BEHIND THEM

Keywords	Justification
NFT	This keyword pertains directly to non-fungible tokens, which are the primary focus of sentiment analysis.
Cryptoart	Cryptoart is digital art connected to non-fungible tokens; analyzing this keyword could disclose insights into the sentiments of the art community.
Bitcoin	As the most popular cryptocurrency, Bitcoin frequently influences the complete cryptocurrency market, including NFTs. Bitcoin sentiment analysis could provide context for market sentiment as a whole.
NFTart	This term combines NFT with art, focusing on the artistic qualities of NFTs.
NFTcollector	This term may assist in evaluating the market's desire and excitement for NFTs.
Ethereum	Ethereum is the most popular platform for creating and exchanging NFTs. Ethereum sentiments may have an influence on the NFT market and its players.
Blockchain	Blockchain is the underlying technology that powers NFTs and cryptocurrencies. Analyzing blockchain emotions might give insights into general confidence and excitement about the technology.
CryptoNFT	This keyword combines the phrases "crypto" and "NFT," and it focuses on the emotion associated with the junction of cryptocurrencies and non-fungible tokens.
Metaverse	The metaverse is a virtual environment in which NFTs are often utilized to store digital assets. Sentiment in the metaverse may influence how NFTs are perceived and valued in this environment.
Opensea	Opensea is a well-known NFT marketplace. Analyzing Opensea sentiment might give information into user experience and market health.
Solana	Solana is a new blockchain platform with increasing NFT usage. Solana sentiment may give insight into the possible development and problems for NFTs on this platform.

Beeple NFT	Beeple is a well-known digital artist whose NFT sales have garnered attention. Analyzing sentiments surrounding Beeple NFTs may show market opinion and the worth of high-profile NFTs.
Tezos	Another blockchain technology focused on efficient and energy-conscious approaches. Analyzing Tezo's sentiment may give insights into the development and acceptance of NFTs among the sustainability community.

3.2.1.2 NFTs' keywords

The following table demonstrates the „NFT keywords" used for data collection. The "chain" describes the blockchain network upon which the NFT is constructed and operates. Ethereum, Binance Smart Chain, Solana, and Ploygon are prominent blockchain networks for NFTs. Each chain has its own distinct characteristics, including transaction fees, transaction speed, and degree of decentralization, which can influence the user experience when buying, selling, or interacting with NFTs on that chain.

The market capitalization (Market Cap) represents the entire market value of a particular NFT undertaking or collection. It is computed by multiplying the present pricing of the NFT by the collection's total number of NFTs. Market capitalization is a means to measure the relative scale and value of a given project, with greater market capitalizations typically indicating more established or significant projects.

The term "category" pertains to the grouping of an NFT initiative based on its subject matter or purpose. Art, gaming, profile pictures (PFPs), sports, collectibles, and virtual land are typical categories of NFT. Inside the broader NFT market, each category pertains to distinct demographics and serves unique functions. And the "creator" is the person, group, or organization tasked with creating, developing, and launching an NFT endeavor or collection. Creators are accountable for the artistic and technical facets of NFTs, along with the project's overall vision and direction. In certain instances, the creator may also serve an ongoing role in administering and maintaining the NFT environment, including updating content, coordinating events, or engaging the community. In addition, a brief summary of each is also provided.

TABLE 3-2- SUMMARY OF NFT KEYWORDS AND JUSTIFICATION BEHIND THEM

Keywords	Chain	Market Cap	Category	Creator	Summary
BAYC NFT	Ethereum	514K ETH	PFPs	Yuga Labs	The Bored Ape Yacht Club is an assortment of 10,000 hand-drawn NFTs depicting various Bored Ape characters. Owners benefit from unique events and membership advantages within the BAYC community.

Keywords	Chain	Market Cap	Category	Creator	Summary
Cryp-toPunks	Ethere um	1M ETH	PFPs	Larva Labs	CryptoPunks is considered one of the pioneering NFT projects, featuring a collection of 10,000 distinct pixel art characters that were algorithmically generated. The NFTs have garnered substantial attention and worth as col-lectible items within the NFT domain.
MAYC NFT	Ethere um	216K ETH	PFPs	Yuga Labs	The Mutant Ape Yacht Club is a deriva-tive of the BAYC idea. The platform showcases a collection of 20,000 exclu-sive Mutant Ape NFTs, each possessing unique characteristics and properties. Additionally, it provides comparable privileges to those of BAYC member-ship.
Azuki NFT	Ethere um	145K ETH	PFPs	TeamAzuki	Azuki comprises a distinctive assem-blage of 10,000 digitally rendered manga characters, each of which is im-bued with a unique hand-drawn quality that draws inspiration from Japanese culture and the aesthetics of manga.
CloneX NFT	Ethere um	57K ETH	PFPs	RTFKT-CLONEXTM	CloneX is a compilation of 10,000 3D av-atars that have been generated pro-grammatically by RTFKT Studios. Virtual worlds and platforms for the metaverse allow owners to utilize their avatars.
DeGods	Ethere um	69.8K ETH	PFPs	DeLabs	DeGods is a generative NFT art en-deavor consisting of 10,000 distinct dig-ital deity characters.
Meebits	Ethere um	43.6K ETH	PFPs	Yuga Labs	Meebits is a compilation of 20,000 dis-tinct 3D voxel characters created by the same team as CryptoPunks. They're in-tended for use in virtual environments, video games, and metaverse platforms.
Sewer Pass	Ethere um	401 ETH	PFPs	Sewer Pass	Sewer Pass is an NFT initiative made up of 9,999 distinct digital sewer rats. In

Keywords	Chain	Market Cap	Category	Creator	Summary
					addition to utilities such as events, merchandise, and community features, proprietors will have access to an online skill-based game developed for BAYC characters that can result in the gaining of rewards that can later be traded or sold.
Moonbirds NFT	Ethereum	26.4K ETH	PFPs	Proof_XYZ	Moonbirds is a compilation of 10,000 hand-drawn, algorithmically generated bird characters. Each Moonbird NFT possesses a distinct set of characteristics and attributes.
The Captainz	Ethereum	78.9K ETH	PFPs	9GAG	The NFT initiative Captainz features 10,000 hand-drawn pirate characters. These NFTs grant their proprietors' access to a pirate-themed virtual metaverse, exclusive events, and community advantages.
Doodles NFT	Ethereum	25.1K ETH	PFPs	Doodles_LLC	There are 10,000 distinct, hand-drawn characters in Doodles. They are intended for use as profile photographs, in virtual environments, and for other inventive applications.
Pudgy Penguins NFT	Ethereum	34.6K ETH	PFPs	TheIgloo-Company	The book Pudgy Penguins contains 8,888 hand-drawn penguin characters. These NFTs have acquired popularity as mementos and works of digital art.
VeeFriends NFT	Ethereum	24K ETH	PFPs	VeeFriends Dev	The entrepreneur Gary Vaynerchuk designed the NFT initiative VeeFriends. It has 10,255 distinct hand-drawn characters, and owners have access to special events, material, and community advantages.
CryptoNinja	Ethereum	24.4K ETH	PFPs	ikehaya_JP	CryptoNinja is a compilation of 10,000 distinct ninja characters generated algorithmically. These NFTs can be used in

Keywords	Chain	Market Cap	Category	Creator	Summary
					virtual environments and games as mementos.
Axie Infinity	Ethereum	11.5K ETH	Gaming	Trung Nguyen	Axie Infinity is a blockchain-based game focused on collectible Axies. Axies can be bred, fought, and traded as non-transferable pets.
Decentraland	Ethereum	56.3K ETH	Virtual World	eodcl	Decentraland is a platform for virtual reality where users can develop, experience, and monetize content and applications. Virtual land and in-game properties in Decentraland are represented by NFTs.
NBA Top Shot	Labs's Flow	209M $	-	Dapper	NBA Top Shot is a blockchain-based marketplace that enables supporters to purchase, sell, and barter NBA collectible highlights as NFTs. Each "moment" depicts a significant play or event from an NBA game.
Rektguy	Ethereum	5.3K ETH	PFPs	rektsafe.eth	Rektguy is a NFT initiative that features 7,777 hand-drawn characters depicting traders who have suffered significant losses in the cryptocurrency market. As mementos and digital artworks, these characters have grown in popularity.
Opepen	Ethereum	4.6K ETH	Art	visualizevalue	Opepen is a collection of 10,000 hand-drawn characters with gaping mouths. These NFTs are intended for use as profile images and for other creative endeavors.
Claynosaurz NFT	Solana	667K SOL	Art	Claynosaurz	Claynosaurz is a collection of 10,000 hand-sculpted, distinctive clay dinosaurs. Each Claynosaur NFT has a distinct combination of characteristics and attributes, functioning as collectibles and works of digital art.

Keywords	Chain	Market Cap	Category	Creator	Summary
Mocaverse	Ethereum	6.6K ETH	PFPs	Mocaverse	Mocaverse is an NFT initiative that features a collection of 9,999 hand-drawn, distinct characters that inhabit the Mocaverse virtual universe. It includes four primary categories of utility, referred to as realms, which represent the collection's central pillars: learn, play, construct, and do good. The realms will facilitate the exchange of ideas, the pursuit of new information, and the expansion of the community.
y00ts	Polygon	20.4K ETH	PFPs	DeLabs	y00ts is a compilation of 15,000 hand-drawn characters representing a new generation of digital creatures created by community members. Within the y00ts ecosystem, members will be able to establish sub-communities, fan art, and even enterprises, thereby enhancing the value of the y00ts NFT collection.
DigiDaigaku	Ethereum	7.4K	PFPs / Gaming	LimitBreak	DigiDaigaku is an NFT initiative comprised of 10,000 hand-drawn characters influenced by Japanese culture, folklore, and anime styles. These NFTs are collectibles and works of digital art and gaming.
SchizoPosters	Ethereum	1.4K ETH	Art	Rivergod	This collection contains one thousand hand-drawn digital poster designs. These collections prioritize emotions over conventional goals, such as launching games or becoming intellectual property (IP) actors and brands.
Holoself	Ethereum	754 ETH	Art/Gaming	Holoself-Deployer	The NFT initiative Holoself is a compilation of 10,000 distinct holographic avatars. It is an addition to the Momoguro NFT collection, which can be used for profile photographs, gaming, and virtual worlds.

Keywords	Chain	Market Cap	Category	Creator	Summary
Mfers NFT	Ethereum	7K ETH	PFPs	Sartoshi	Mfers is a compilation of 10,000 hand-drawn, distinctive characters. These NFTs are intended for use as profile photographs, and their value rests in the community with which they are associated.
Ethlizards	Ethereum	3.5K	PFPs	ETHLIZARDS	Ethlizards is a compilation of 10,000 hand-drawn reptiles with varying features and characteristics. In the NFT space, these NFTs function as collectibles and digital art.

3.2.2 Data Collection from Twitter

3.2.2.1 Twitter API for data extraction

Twitter is fundamentally about sharing opinions and starting conversations about politics, culture, employment, industries, brands, and other topics. Consequently, Twitter is a treasure trove of data for sentiment analysis, prediction, and more. Essentially, businesses may utilize Twitter to discover significant trends, learn what people think about particular goods, campaigns, and topics, and develop solutions based on these findings to boost the likelihood of success.

According to Twitter, the Twitter API is an endpoint that can be utilized to "programmatically retrieve and analyze Twitter data, as well as build for the conversation on Twitter." (*Getting Started with the Twitter API*, 2023) With Twitter's API, scientists and programmers can use the platform's data to create new applications or conduct additional research.

Late in 2021, Twitter released version 2.0 of its Twitter developer system API. Now, there are three levels of access: basic, elevated, and scholarly. The free basic level permits the scraping of 500,000 tweets per month and includes one app environment. The free elevated level includes three app environments and allows users to collect up to 2 million tweets per month. The academic level permits users to collect up to 10 million tweets per month and conduct sophisticated searches (*Build Whats next with the New Twitter Developer Platform*, 2023). To be accepted to the academic level, nevertheless, one must fulfill their stringent requirements.

After receiving the API tokens, one can begin retrieving data from Twitter. There are numerous methods to accomplish this. Utilizing the official API documentation is one option. This investigation obtained all messages via the Twitter API with academic-level authorization. This is the maximum level of access, which allows us to collect up to 10 million tweets per month and conduct advanced searches. This level of access enables a user to collect messages older than ten days.

3.2.2.2 Time frame and volume of data collected

The period between 15th March till the end of May has been chosen as our research period. During this period, up to 1 million Tweets containing any of the abovementioned words have been crawled. The period selected has an important function in the research as it provides enough time to observe stakeholder reactions to specific news or change. Also, in this period, several noteworthy events have rattled the cryptocurrency and NFT market, from the U.S. government conundrum with crypto legislation (Bland, 2022) to Elon Musk's Tweets (Shahzad et al., 2022) to Pudgy Penguins raising $9M as seed funding ("MetaversePost on Binance Feed: Pudgy Penguins Makes Bigger IP Play With $9M Raise in Seed Round Led By 1kx | Binance Feed," 2023).

Notably, no retweets were gathered as we only wanted to keep a dataset with original tweets. As well, all tweets should have been identified as being written in English by Twitter. In addition to the tweet itself, multiple additional metrics, including the tweet ID, were collected to identify the tweet. The tweet's posting date was collected in order to undertake a temporal analysis. The username was saved in order to verify the data.

3.2.3 Sentiment analysis

Sentiment analysis seeks out opinions, evaluates the way they are expressed, and determines the text's universal polarity on the spectrum from positive to negative. Furthermore, it employs a comparable strategy at the level of individual emotions. Medhat et al. provided a summary of the various sentiment algorithms and usage (Medhat et al., 2014). They divide sentiment detection methods into two main categories: machine learning and lexicon-based methods, as is explained widely in the literature section. Approaches utilizing machine learning handle language characteristics in a supervised or unsupervised manner, whereas lexicon-based approaches rely on collections of sentiment terms with known orientations. Both are divisible into lower-level divisions. Thus, lexicon-based methodologies are subdivided into dictionary-based methodologies and corpus-based methodologies. As corpus-based approaches require large quantities of text to enrich an initial list of phrases expressing an opinion, machine learning techniques also rely on sizable corpora. The proposed methodology for this study is dictionary-based. External validity has been established through validation experiments that demonstrate a strong correlation between the methods used to create dictionary categories with emotionally charged phrases and trained judges' evaluations (Hirsh & Peterson, 2009). Lexicon-based techniques are supported by hundreds of research connecting, for instance, LIWC categories with various psychological processes and agreement rates ranging from 93% to 100% amongst various sets of judges (Scholand et al., 2010). Similarly, Mohammad and Turney discovered that at least four of the annotators agreed on more than 80% of the words in the NRC (National Research Council Canada) and that five distinct annotators agreed on more than 60% of the terms (Mohammad & Turney, 2013). They infer that 'even nevertheless emotions are naturally subjective, there is an acceptable level of consensus on word emotion associations' based on their assessment that Best-Worst-Scaling is more reliable than commonly used ratings from current lexica.

3.2.3.1 Dictionary selection

The NRC Emotion Lexicon (EmoLex) created by Mohammad and Turney (2013) is utilized to recognize the emotions conveyed in the Tweets. The EmoLex relies on the concept of fundamental emotions. The team of researchers chose to employ Plutchik's eight fundamental emotions: sadness and joy, fear and anger, trust and disgust, and anticipation and surprise. The basic premise is that all conveyed emotions can be categorized under one of the eight fundamental emotions. To characterize these emotions, Mohammad and Turney allowed respondents to attribute 14,182 terms to one or more of these eight sentiments using Amazon's Mechanical Turk (Mturk). Furthermore, every word had to be allocated to either the positive or negative sentiment. The thereby created EmoLex is accessible in 105 languages.

In the present research, the English version was utilized to figure out, first, which emotions emerge in which evaluations and, second, which emotions are activated by the aforementioned Tweets. In the end, tstring-matching produced a matrix with the number of matches in each cell, sized 5.875 (lemmatized aggregated EmoLex terms) x 983.385 (English Tweets).

3.2.4 Financial Data on NFTs

OpenSea, CoinGecko, and CryptoSlam are used to collect associated market information and price charts for each studied NFT.

3.2.4.1 OpenSea

OpenSea serves as one of the most prominent and well-known NFT exchanges. It was established in 2017 by Alex Atallah and Devin Finzer, runs on the Ethereum blockchain, and provides a variety of non-fungible token categories, such as art, gaming, virtual world objects, trading cards, and more (Bhardwaj et al., 2023). OpenSea supplies a vast multitude of data regarding each NFT, such as its pricing history, ownership information, and volume of trading. This renders it an indispensable tool for data collection and research.

3.2.4.2 CoinGecko

CoinGecko is a data platform for cryptocurrencies that was founded in 2014. It offers real-time and archival data on over 6000 digital currencies from over 400 exchanges. The platform provides information such as transaction volume, market capitalization, and coin comparison, among other things ("About CoinGecko," 2023). CoinGecko is especially useful for analyzing the correlation between the prices of NFTs and cryptocurrencies. Since the majority of NFT transactions are conducted with cryptocurrencies (particularly Ether), CoinGecko's extensive crypto price data are able to provide crucial context for comprehending NFT market dynamics.

3.2.4.3 CryptoSlam

CryptoSlam is a data collection and analytics platform for NFTs and crypto collectibles. The website was established by Randy Wasinger in 2018 and has evolved to become a pioneer in NFT data analytics (*CryptoSlam! NFT Data, Rankings, Prices, Sales Volume Charts, Market Cap*, 2023). CryptoSlam offers extensive data for multiple blockchains, such as Ethereum, Flow, WAX, and

Binance Smart Chain. CryptoSlam enables real-time monitoring of transactions of non-fungible tokens, which is essential for understanding the present trends and characteristics of the non-fungible token market. It provides information on each NFT project's volume of sales, highest sales, median price, number of purchasers, and more. In addition, it lists NFT projects according to their sales, providing a snapshot of which projects are market leaders. Additionally, CryptoSlam offers data visualizations and statistics for specific NFT initiatives. These can be used to examine price fluctuations and trading volume over time. This information is especially beneficial for researchers who wish to model and forecast NFT prices.

3.3 Data analysis

Because of its strong capabilities in managing huge datasets and conducting extensive statistical analyses, the data were analyzed using the R programming language. Several statistical approaches were used in the analysis process, ranging from basic techniques like descriptive statistics to more complicated analyses like regression and correlation algorithms.

To begin, descriptive statistics were used to offer a high-level summary of the data's features. This comprised central tendencies and dispersion estimations. These fundamental statistics served as the dataset's underlying knowledge, illustrating the overall trend and variability.

Following the descriptive analysis, the variables' associations were assessed using Spearman's rank correlation. This non-parametric measure offers a viable tool for investigating relationships while making no assumptions about the distribution of the data. The Spearman's correlation analysis findings assisted in identifying variables with strong monotonic correlations. To graphically portray the data, graphical approaches such as scatter plots and boxplots were used. Scatter plots provided a graphical depiction of the connections between variables, while boxplots provided information about the data distribution, indicating probable outliers.

The investigation then moved on to regression modeling. To explore how one or more independent variables may explain the dependent variable, multiple linear regression analysis were performed. This improved the capacity to anticipate and comprehend the cause-effect linkages between the variables.

Finally, VAR is a statistical technique for multivariate time series forecasting that is employed in situations where two or more time series exhibit interdependence. The model's variables exhibit interdependence, whereby they are not solely reliant on their preceding values but also on the other variables present within the system. This approach facilitates the acquisition of linear interrelationships among numerous variables.

3.4 Conclusion

This chapter offered the full methodology used in this study, which included the research design, data gathering procedure, and data analysis methodologies. Initially, the study used a quantitative approach, concentrating on the collection of numerical data and subsequent statistical analysis. The datasets were obtained from credible sources, with a detailed explanation of the variables of interest and data extraction processes.

The study's aims, notably the goal of uncovering important linkages and patterns within the gathered data, prompted the selection of the research design. The systematic and rigorous use of the R programming language for data administration and analysis aided this approach. A range of statistical methods were employed, varying from fundamental descriptive statistics to complex techniques such as regression analysis and generalized linear models. Each approach contributed uniquely to the investigation and comprehension of the information, offering both a descriptive and inferential viewpoint.

Finally, this chapter has provided a blueprint for how the study was carried out, so ensuring the reliability and repeatability of the research results. The next chapters will give the findings and interpretations based on the approaches outlined above, bringing to light the insights garnered from the data.

4 RESULTS AND DISCUSSION

4.1 Introduction

This chapter concentrates on the representation, examination, and interpretation of the data collected for this study. OpenSea, CoinGecko, CryptoSlam, and Twitter data provide a full panorama of the NFT industry, including significant companies and prominent trends. The combination of these datasets enables us to go beyond a straightforward descriptive study. We will go further, investigating the complicated links between many components of the NFT market and online opinion. Correlations based on each mood and those found across multiple NFT marketplaces will be the two key topics of attention. This dissection attempts to discover deep understandings and produce significant insights regarding the NFT market dynamics.

We believe that by putting our insights together, we may develop an educated view of the NFT industry, enlightening stakeholders and supporting strategic decision-making in this fascinating and expanding sector.

4.2 Presentation of Collected Data

4.2.1 Description of the collected data from OpenSea, CoinGecko, CryptoSlam, and Twitter.

Through the data collection phase from Twitter, 983,358 tweets were crawled. The following tables summarize them based on the keywords and the categories.

TABLE 4-1- NUMBER OF TWEETS CRAWLED VIA GENERIC TERMS KEYWORDS

Generic terms	**Tweets crawled**
NFT	27,611
Cryptoart	28,921
bitcoin	31,548
NFTart	30,275
NFTcollector	29,653
Ethereum	26,898
blockchain	26,909
cryptoNFT	29,807
Metaverse	27,080
Opensea	26,96

Solana	33,20
Beeple NFT	26,249
Tezos	23,664

TABLE 4-2-NUMBER OF TWEETS CRAWLED VIA NFTS KEYWORDS

NFTs	**Tweets crawled**
BAYC NFT	26,117
CryptoPunks	28,928
MAYC NFT	25,554
Azuki NFT	24,624
CloneX NFT	16,552
DeGods	27,709
Meebits	28,884
Sewer Pass	10,211
Moonbirds NFT	30,140
Captainz	32,016
Doodles NFT	27,021
Pudgy Penguins NFT	5,223
VeeFriends NFT	16,032
CryptoNinja	17,781
Axie Infinity	25,334
Decentraland	29,038
NBA Top Shot	13,113
Rektguy	16,577
Opepen	23,235
Claynosaurz NFT	25,431
Mocaverse	13,349

y00ts	33,908
DigiDaigaku	28,335
SCHIZO_POSTERS	26,589
Holoself	2,768
mfers NFT	31,048
Ethlizards	24,826

The data collection was conducted from 03/13/2023 to 05/04/223. Similarly, Market Capitalization (MC) for traded NTFs is also extracted from the from OpenSea, CoinGecko, and CryptoSlam websites (Figure 4-1). The level of market turbulence seems to be adequate, indicating the nature of NFT markets and different trends.

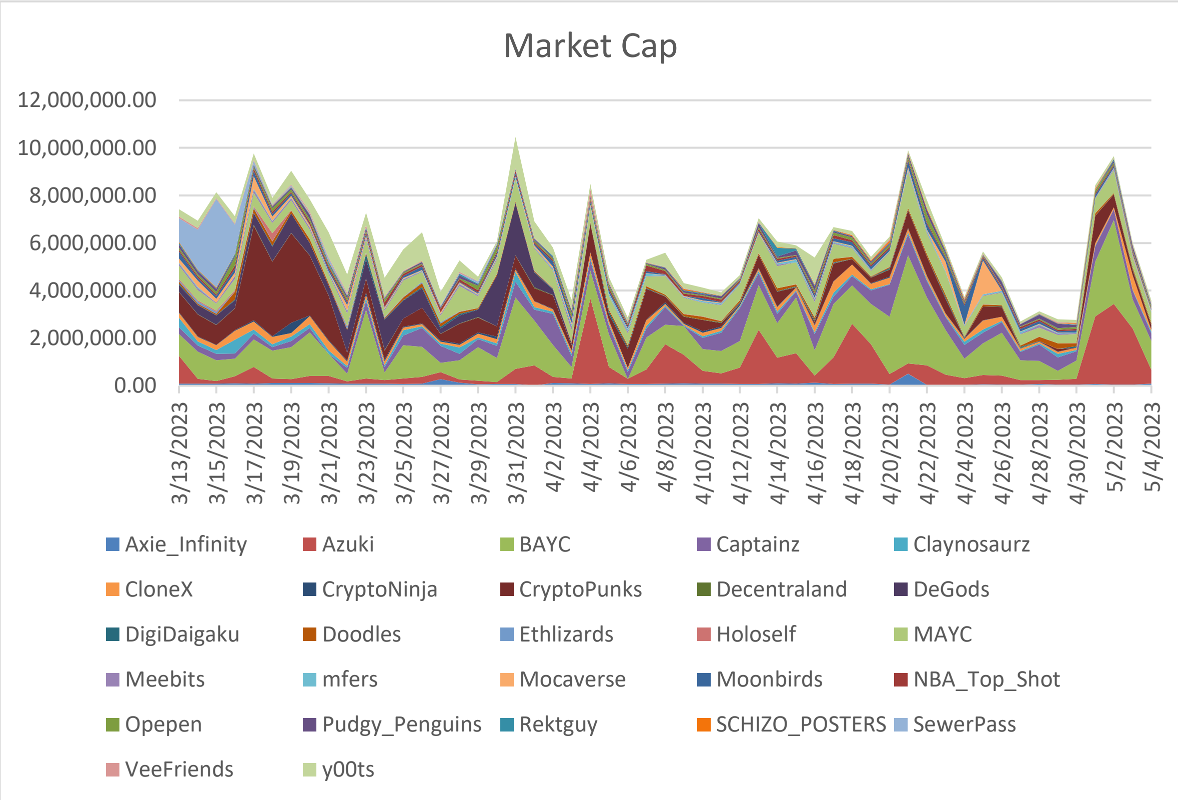

FIGURE 4-1- MARKERCAP CHART FOR EACH NFT

Similarly, historical MC values for three prominent coins are also studied, which can be useful in the study of NFT market trends and possible causes of the bull and bear waves. Moreover, Fig. 4-2 demonstrates the extracted sentiment from tweets regarding Axie_Infinity NFT during the observation period. This is an example of the conducted study on each NFT. This graph depicts the sentiment analysis of almost a month and a half, from March 13, 2023, to May 4, 2023. Anger, anticipation, disgust, fear, joy, sadness, surprise, and trust are the eight emotion categories that are often utilized in sentiment analysis. It is clear that anticipation and trust continuously have the greatest values among the feelings, showing a generally optimistic mood in Axie Infinity tweets. The amount of tweets in negative categories like anger, disgust, and fear is often lower than in good categories like anticipation and trust, but it does peak on particular occasions. Throughout this time span, the general emotion is more positive than negative, as evidenced by the final two rows.

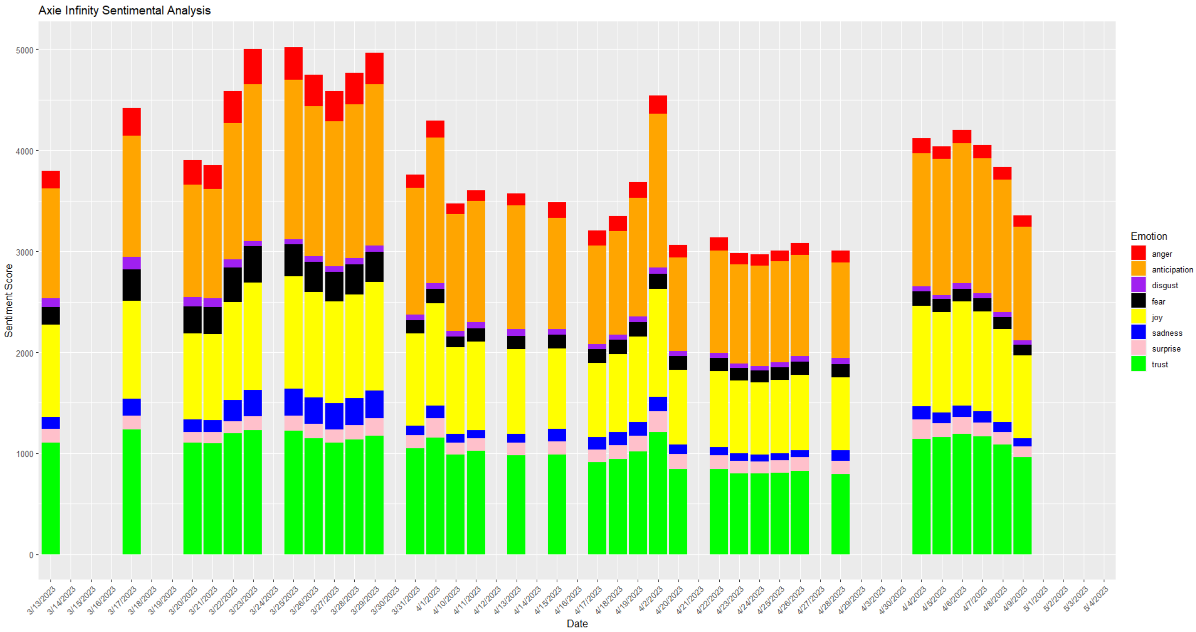

FIGURE 4-2- CRAWLED SENTIMENTS REGARDING AXIE INFINITY DURING THE STUDY PERIOD

Similarly, Figure 4-3 showcases the extracted sentiments regarding one of the generic keywords, "Beeple." The data depicted in the figure indicates that positive sentiments, namely joy, trust, and anticipation, show a greater frequency of mentions on Twitter in comparison to negative emotions, such as anger, disgust, and fear. This pattern seems to be continuous over the time span. The number of tweets indicating joy, anticipation, and trust boosted significantly at the start of the period and remained reasonably high throughout, with a little dip near the end of April 2023. This shows that the general attitude towards Beeple was largely good throughout this time period. Additionally, negative attitudes such as anger, disgust, and fear rose with time but remained comparatively lower compared to good sentiments. Furthermore, towards the conclusion of the term, the counts of both positive and negative feelings seem to diminish. This might indicate a drop in general interest or involvement with the issue, or it could be an artifact of the data gathering or analysis process.

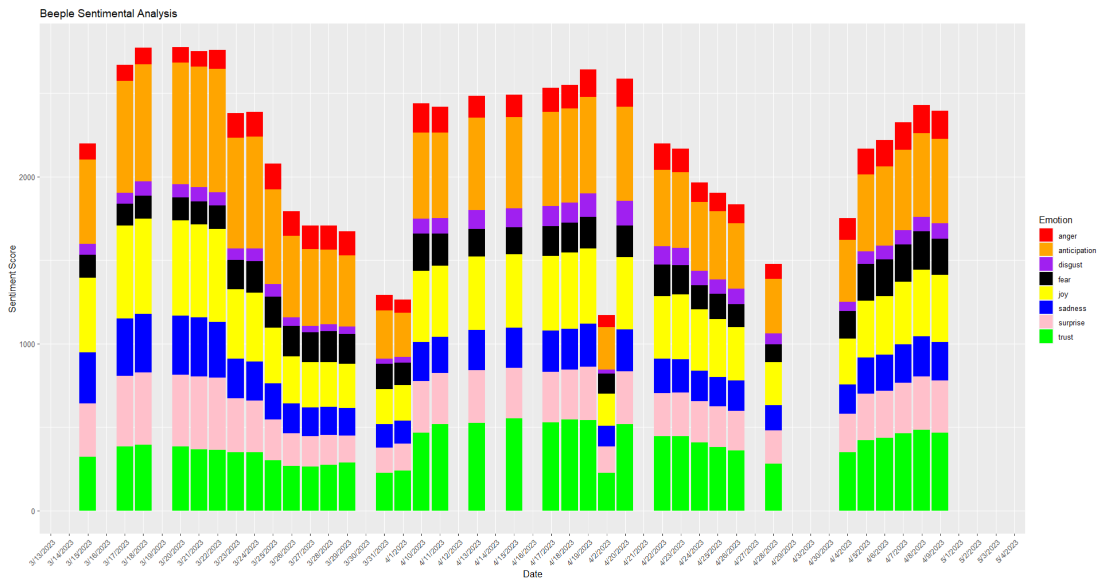

FIGURE 4-3- CRAWLED SENTIMENTS REGARDING BEEPLE KEYWORD DURING THE STUDY PERIOD

Figure 4-4, demonstrates the heat map associated with a different sentiment and their intensity toward each study's NFTs during the study period. The given Figure and associate table (Appendix 1) provide a compelling analysis of various emotional trends across several NFT projects. The figure provides an intriguing understanding of the emotional terrain that envelops these endeavors, investigating the pervasiveness of a range of emotions, including but not limited to anger, anticipation, disgust, fear, joy, sadness, surprise, and trust, in addition to general positive and negative sentiments. Commencing with the sentiment of displeasure, NBA_Top_Shot appears to elicit a considerable degree of this affective state, as evidenced by a tally of 15,560, suggesting a certain level of discontent or vexation among its user base. On the opposite side of the continuum, Holoself exhibits the minimum count, indicating a comparatively diminished prevalence of this sentiment among its populace.

The game Axie_Infinity has garnered significant attention, as evidenced by a count of 41,807, indicating a strong feeling of anticipation and excitement among its followers. In contrast, it can be observed that the Holoself project exhibits the lowest level of anticipation, which may suggest a comparatively lower degree of engagement or excitement. The Sewer-Pass project has garnered a significant count of 11,609 in the disgust category, indicating a prevalence of unfavorable responses towards it. The Holoself system registers the minimum threshold of emotional manifestation, denoting limited displays of said emotion. The project NBA-Top_Shot has garnered a significant count of 15,691 in relation to fear, which may suggest the presence of underlying anxieties or concerns surrounding the initiative. Holoself is once again credited with the determination of the least count.

Axie_Infinity has received the highest number of mentions, totaling 30,470, indicating a significant level of pleasure or satisfaction among its audience in relation to the joy emotion. On the contrary, Holoself exhibits the lowest level of happiness. The affective state of sadness is observed to be particularly salient in the context of NBA_Top_Shot, with a numerical count of

14,947, whereas Holoself exhibits the lowest count in this regard. The aforementioned observation implies a range of affective encounters associated with the NFT initiatives, encompassing a gamut of emotions from elation to melancholy.

In regards to the concept of surprise, NBA_Top_Shot continues to rank highly, indicating a significant level of unforeseen events or disclosures associated with it. In contrast, the Holoself displays the lowest numerical value. Axie_Infinity is the leading project in the trust category, with a significant count of 35,443. This count suggests a high level of confidence and reliability associated with the project. In contrast, Pudgy-Penguins has the lowest recorded count.

Upon analyzing the general sentiment, it can be observed that Axie_Infinity has obtained the most significant number of affirmative emotions, indicating a predominant optimistic sentiment. Pudgy-Penguins, on the other hand, display the lowest frequency. On the contrary, NBA_Top_Shot is predominantly linked with negative sentiments, whereas Pudgy-Penguins exhibits the lowest occurrence of negative emotions.

In summary, the examination of emotional patterns across diverse NFT initiatives provides significant and indispensable perspectives. While certain initiatives such as Axie_Infinity are widely embraced with a considerable degree of favorable sentiment, others such as NBA_Top_Shot tend to elicit more ambivalent or unfavorable responses. The emotional terrain outlined below is a crucial contextual factor for stakeholders involved in NFTs as it aids in comprehending the community's sentiment and devising future plans.

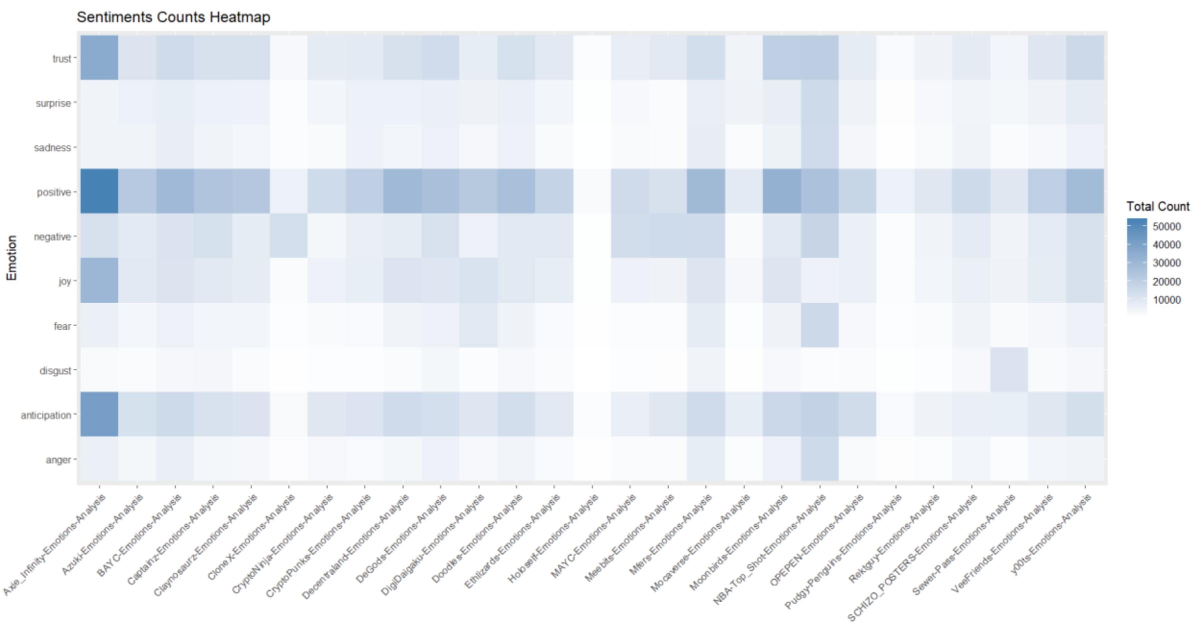

FIGURE 4-4- NFTS SENTIMENT COUNT HEATMAP

Later in this section, we will briefly discuss prominent events that happened in the market to have an overview of the NFT market trend and to further analyze the possible associations between changes of sentiments through the period.

4.3 Overview of the NFT market trends and key players.

NFTs have risen as a prominent trend in the quickly changing digital landscape, revolutionizing several sectors such as art, entertainment, and real estate. In recent months, the NFT market has experienced notable transformations, characterized by the emergence of fresh market participants, dynamic trends, and heightened impact from overarching factors such as technology behemoths and the general state of cryptocurrency trading. This section provides an in-depth analysis of recent developments in the NFT marketplace, including the evolving dynamics, shifts in demand for NFTs, dominance of select projects, significance of trading volume for project durability, liquidity trends, and the potential influence of major corporations such as Amazon Web Services (AWS). Additionally, this paper will examine the obstacles encountered by the cryptocurrency industry in the United States and their potential impact on the NFT ecosystem.

Since its introduction and airdrop on February 15, 2023, Blur has emerged as a significant contender in the NFT marketplace, exceeding OpenSea in both trading volume and royalty share of the market. The vast majority of traders on Blur are characterized as professional traders who engage in high-frequency trading and execute trades with an average amount per trade. Since mid-February 2023, OpenSea and Blur have been engaged in a "royalty war", with the latter's low fees proving to be an attractive proposition for users. In response, OpenSea has temporarily eliminated marketplace fees.

Furthermore, there is a decrease in demand for lower quality sets in the NFT market. Over the preceding quarter, half of the NFT projects that lacked liquidity exhibited a minimum price range of 0 to 0.5ETH (“Why NFTs Are Dying? Is the Hype around NFTs Dead?,” 2023).

Although comprising less than 1% of the overall number of projects, the top 50 NFT initiatives possess a MC equivalent to approximately 52% of the total. These initiatives hold a significant market share, indicating the impact of "whales" or prominent investors in the field. It has been observed that projects which attain a trading volume of 1000 ETH or higher exhibit increased resilience and are able to capture a greater portion of the market. Likewise, endeavors that attain a 7-day trading volume of 10,000 ETH are included in a select cohort of preeminent undertakings that hold sway over the market (CoinMarketCap, 2023).

The NFT market demonstrated its highest level of liquidity during the period spanning from January to April of 2022. However, a notable decline was observed in May 2022, with a subsequent recovery observed only in the initial half of 2023. The degree of liquidity is significantly associated with the market's level of popularity and the frequency of trading activities performed by traders (CoinMarketCap, 2023).

In addition, regarding the influence of major corporations and the wider cryptocurrency industry on NFTs, it is noteworthy that AWS has evinced an avid interest in blockchain technology, thereby holding the potential to exert an impact on the NFT market. According to the news (CoinMarketCap, 2023), AWS has been engaged in different blockchain-related initiatives, including the introduction of its Managed Blockchain service and the development of a Blockchain Templates offering. The aforementioned indicates that Amazon is acknowledging the potential of blockchain technology in diverse domains, such as decentralized gaming and in-game assets.

Additionally, within the United States, the cryptocurrency market has encountered numerous challenges that have impacted the NFT market. The NFT market, which has been expanding at a swift pace, has encountered the common obstacles that the wider cryptocurrency market has confronted. The crypto market is currently facing regulatory scrutiny, as U.S. authorities are taking measures to address concerns regarding potential fraud and tax evasion (Bland, 2022). One noteworthy example of the challenges faced by the cryptocurrency market in the United States and their impact on the NFT space is exemplified by the BAYC case. The BAYC is an NFT initiative that has achieved noteworthy progress in the industry, having vended numerous one-of-a-kind digital primates and generating a substantial amount of income. BAYC made the decision to resettle its operations to Puerto Rico, a jurisdiction known for its serviceable stance towards cryptocurrency, as a result of the ambiguous regulatory environment in the United States. The objective of this action was to safeguard the assets of the project and sustain its activities within a regulatory environment that is less adversarial. This instance exemplifies the influence of the challenges faced by the cryptocurrency market in the United States on the NFT industry.

Notwithstanding the obstacles, the NFT market has demonstrated tenacity and persists in flourishing. Prominent NFT initiatives sustain a specific degree of fluidity and demonstrate reduced instability, whereas the fluidity of less prominent initiatives tends to gradually diminish following their release and become highly vulnerable to market fluctuations. Several of these initiatives, including BAYC and others, have been able to sustain profitability over a considerable duration despite the current market circumstances.

To encapsulate, the NFT market is subject to various influences, such as the condition of the wider cryptocurrency market, the regulatory landscape, and the approaches adopted by specific NFT initiatives. Notwithstanding the obstacles, the market persists in undergoing transformation and adjustment, as evidenced by the emergence of novel platforms such as Blur and the demonstration of resilience by significant initiatives in the face of adversity. The trajectory of the NFT market is expected to be significantly impacted by advancements in the wider cryptocurrency market and the regulatory framework in critical regions such as the United States.

4.4 Correlation Analysis

This section focuses on conducting a correlation analysis to investigate the association between sentiment scores attributed to individual NFTs and the corresponding market data, especially MC. The present study offers an analysis that sheds light on the correlation between the sentiment pertaining to NFTs and their market performance. Via a study of the relationship between sentiment ratings and MC, a more in-depth understanding of the variables that affect market interactions can be earned. This analysis may also facilitate the identification of patterns or trends that have an effect on the value of NFTs.

First, to have an overview of the association between each sentiment and the MC for all studied 27 NFTs, a grid of bar charts has been developed (Figure 4-5) using Spearman correlation.

4.4.1 Analysis based on each sentiments

Having said that, Figure 4-5 demonstrates the correlation between daily percentage of each sentiment for all NFTs with the associated MCs. The correlation coefficient is a statistical measure employed to evaluate the degree and direction of a link between two different variables (Schober et al., 2018). The correlation coefficient is a numerical statistic with a range of -1.0 to 1.0. A correlation value of one indicates a perfect positive relationship, whereas a coefficient of minus one indicates a perfect negative relation. A correlation coefficient of 0 indicates no relationship between the variables. Regarding anger emotions, the NFT exhibiting that the highest positive correlation is OPEPEN, with a correlation coefficient of 0.395. The data indicate that a rise in OPEPEN-related tweets expressing anger is positively correlated with a corresponding increase in its MC. Holoself exhibits the most substantial negative correlation among NFTs, with a correlation coefficient of -0.269. The findings indicate that a rise in expressions of anger in tweets pertaining to Holoself is generally associated with a decline in its MC. The majority of NFTs exhibit positive correlations, indicating that a rise in anger sentiment expressed in tweets is typically linked to a rise in MC. It is crucial to mention that the presence of correlation does not necessarily imply causation, since there may also exist additional variables that are contributing to the observed phenomenon. The correlation coefficients pertaining to the NFTs exhibit a relatively low magnitude, indicating a weak association between the sentiment of anger in tweets and the MC for all the NFTs that have been enumerated.

As expected, a significant number of NFTs featured in this list exhibit a negative correlation with regards to the expression of disgust sentiments. The aforementioned statement suggests that a rise in the expression of repugnance in Twitter posts concerning NFTs frequently corresponds with a decline in their overall market valuation. The NFT CryptoNinja exhibits a significant negative correlation of -0.477, indicating that an increase in disgust sentiment conveyed in tweets pertaining to CryptoNinja is associated with a decline in its MC. On the contrary, some non-fungible tokens exhibit a modest association. Captainz exhibits a correlation coefficient of 0.0809, suggesting that an upsurge in disgust sentiment expressed in tweets could not be linked to a growth or decline in its MC, as the correlation coefficient is close to zero exhibiting no relationship between the two variables, MC and emotion.

Furthermore, with regards to fear-based emotions, a cursory examination of the data indicates that the majority of non-fungible tokens exhibit an inverse relationship between fear sentiment expressed in tweets and their corresponding MC. The aforementioned, a rise in fear sentiment in tweets linked to NFTs is typically accompanied by a decline in their MC. The NFT Azuki displays a noteworthy negative correlation of -0.503, indicating that a rise in fear sentiment in tweets associated with Azuki is generally linked with a decline in its MC. Nevertheless, certain non-fungible tokens exhibit a positive correlation. As exemplified by OPEPEN, there exists a correlation of 0.238, suggesting a probable association between heightened fear sentiment in tweets and a rise in the MC of the company. It is critical to recognize that the abovementioned correlations have medium to weak links, considering that many coefficients are near to zero. The correlation between the sentiment of fear expressed in tweets and the MC of NFTs appears to be relatively tenuous.

Upon scrutinizing the data pertaining to the joy sentiment, it can be observed that a majority of the NFTs exhibit a positive correlation. This implies that there exists a proclivity for the MC of these NFTs to escalate with a rise in the joy sentiment expressed in tweets pertaining to them. The NFT Sewer_Pass exhibits a strong positive correlation of 0.435, suggesting that its MC tends to rise in tandem with an upsurge in positive sentiment associated with joy. In contrast, certain NFTs, namely Axie_Infinity and DeGods, demonstrate an inverse relationship, whereby their MC has a tendency to decline in response to an increase in positive sentiment expressed in tweets pertaining to them. Nevertheless, the aforementioned adverse associations exhibit a degree of feebleness. In general, there seems to be a positive correlation between the expression of joy in tweets related to NFTs and their corresponding MC. The degree of correlation among various NFTs exhibits considerable variation, and in every instance, the associations are comparatively feeble.

Furthermore, early data on the link between sadness and other factors show a mix relationships directions. The study reveals that certain NFTs, namely Axie_Infinity and Doodles, demonstrate a positive correlation between the sentiment of sadness in tweets associated with them and their MC. Especially, an upsurge in the former is typically associated with an increase in the latter. The analysis indicates that Doodles exhibits a strong positive correlation of 0.460, implying that its MC has a tendency to increase in response to tweets expressing a negative sentiment. Conversely, several non-fungible tokens, such as Claynosaurz and Sewer_Pass, exhibit an inverse relationship. The aforementioned statement suggests that a rise in the expression of sadness sentiment in tweets pertaining to the aforementioned NFTs is frequently associated with a decline in their MCs. The variable Sewer_Pass exhibits a negative correlation of -0.300, indicating that there is a tendency for its MC to decline in response to an increase in the expression of sadness within tweets pertaining to it. In the dataset, there is a lack of a definitive overarching pattern indicating a positive or negative correlation, as both types are nearly equally represented. The findings indicate that there exists a significant variability in the association between the expression of sadness sentiment in tweets and MC across diverse non-fungible tokens.

Upon analyzing the data in the context of surprise sentiments, it can be observed that the majority of the NFTs display a positive correlation. The aforementioned observation implies a positive correlation between the sentiment of surprise expressed in tweets pertaining to the NFTs and their corresponding MC, albeit with varying degrees of magnitude. The analysis reveals that Sewer_Pass exhibits a robust positive correlation of 0.439, suggesting a moderately strong association between a rise in surprise sentiment and its corresponding MC. NBA_Top_Shot and BAYC exhibit correlation coefficients of 0.396 and 0.359, respectively. Conversely, a small number of non-fungible tokens, namely Axie_Infinity and Holoself, exhibit a negative correlation. The aforementioned statement suggests that a rise in the sentiment of surprise observed in tweets linked to the NFTs is generally associated with a decline in their MC. It is noteworthy that the aforementioned adverse correlations exhibit a relatively low magnitude. In general, a positive correlation can be observed between the sentiment of surprise expressed in tweets pertaining to NFTs and their corresponding MCs. The observed correlations exhibit a dispersed distribution, indicating heterogeneous levels of impact of unexpected sentiment on the MC of distinct non-fungible tokens.

After conducting an evaluation of the trust data, it is evident that a majority of the non-fungible tokens exhibit a negative correlation. The statement suggests that a rise in trust sentiment expressed in tweets regarding NFTs is frequently accompanied by a decline in their MC. It is noteworthy that Captainz exhibits the most significant negative correlation, with a value of -0.515. This suggests a moderate inverse association between the trust sentiment and its MC. Doodles and SCHIZO_POSTERS are among the NFTs that exhibit significant negative correlations. Conversely, certain NFTs such as Holoself, Meebits, and Claynosaurz exhibit a favorable correlation, indicating that an upsurge in trust sentiment expressed in the related tweets corresponds to a rise in their MC. Nevertheless, the correlations exhibit a relatively low magnitude, indicating a restricted relationship between the two variables. Overall, a moderate negative correlation appears to exist between the sentiment of trust expressed in tweets pertaining to NFTs and their corresponding MCs. The range of correlation coefficients suggests that the impact of trust sentiment on the MC of different NFTs varies to a certain extent.

Regarding the aspect of anticipation, a considerable number of NFTs display negative correlations, indicating that a rise in the sentiment of anticipation expressed in tweets concerning these NFTs is linked to a decline in their MCs. The NBA_Top_Shot NFT exhibits a notably robust negative correlation of -0.561. Several NFTs exhibit notable negative correlations, such as OPEPEN, Pudgy_Penguins, and Mfers. Conversely, certain NFTs such as Azuki and SCHIZO_POSTERS exhibit a favorable correlation, indicating that a surge in the sentiment of anticipation in tweets pertaining to these NFTs is inclined to coincide with a rise in their MCs. However, the observed correlations exhibit a relatively low magnitude, suggesting a limited association between the variables. In general, it can be observed that there exists a proclivity towards an inverse relationship between the sentiment of anticipation expressed in tweets pertaining to NFTs and their corresponding MCs. It can be inferred that elevated levels of anticipatory sentiment may not necessarily result in a commensurate rise in MC for the non-fungible tokens in question.

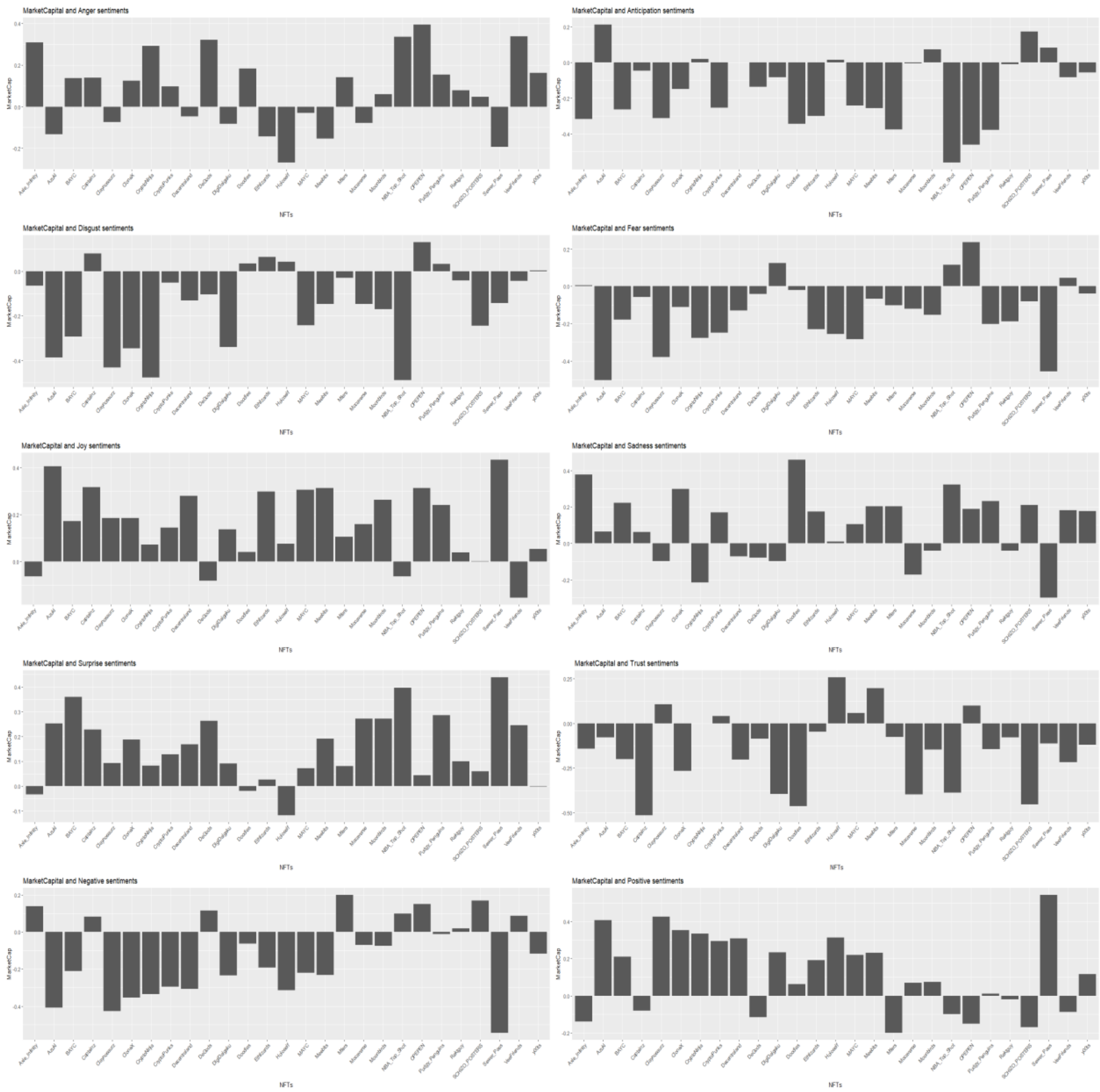

FIGURE 4-5- CORRELATION BETWEEN EACH SENTIMENTS EXTRACTED FROM TWEETS ASSOCIATED WITH SPECIFIC NFT AND THEIR MC

When it comes to negative feelings, the majority of the NFTs show a negative correlation, implying that a rise in the sharing of negative sentiment in tweets regarding these NFTs is often connected with a reduction in their MCs. Sewer_Pass, in particular, has the greatest negative correlation at -0.545, showing a significant inverse association between negative sentiment and its market value. Azuki, Claynosaurz, and CloneX are three more NFTs with substantial negative correlations. In contrast, other NFTs, such as Axie_Infinity, Captainz, and Mfers, show a positive correlation, showing that as negative sentiment in tweets regarding these NFTs grows, so does their market value. These correlations, nevertheless, are quite modest, indicating a weak relationship between the variables. In general, the data indicates a minor negative association between unfavorable sentiment in tweets concerning NFTs and their MCs. The correlation coefficients span a wide range, indicating the varying degrees of effect that negative sentiment may have on the market value of different NFTs.

The majority NFTs, on the other hand, exhibit a positive connection with positive feelings, implying that an increase in favorable sentiment in tweets regarding these NFTs is associated with a rise in their MCs. The NFT Sewer_Pass has the strongest positive correlation (0.545), showing a significant association between positive sentiment and MC. Azuki, Claynosaurz, and CloneX are three more NFTs with significant positive associations. Some NFTs, on the other hand, have a negative correlation, meaning that as positive sentiment in tweets regarding these NFTs grows, their market value tends to fall. These correlations, similar to negative sentiments, are quite modest, indicating a weak relationship between the variables. In general, the data reveals a little positive association between favorable mood in tweets regarding NFTs and their MC. The correlation coefficients span a broad range, indicating the varying degrees of effect that positive sentiment may have on MC across distinct NFTs.

4.4.2 Analysis of different NFT markets

The goal of this section is to provide an overview picture and find notable correlations between sentiments extracted and MC time series. Accomplishing this will not only give us a good understanding of similarities and dissimilarities of different NFT markets, but also can provide us with the strongest correlations which later could be integrated to develop a predictive model. The correlation matrices shown below reflect correlations between daily percentages of various emotions collected from tweets linked with various NFTs and their MC.

4.4.2.1 Azuki

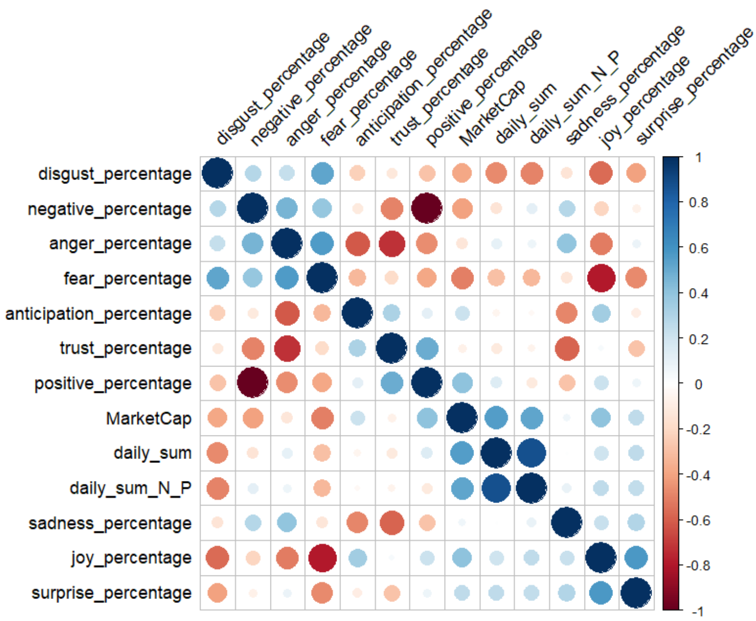

FIGURE 4-6- CORRELATION MATRIX: AZUKI- SHOWING THE CORRELATION AMONG DIFFERENT SENTIMENTS AND MC

Azuki, as demonstrated in the Figures 4-6 and 4-7, seems to have the high number of significant correlations with different sentiments and the MCs. Significant positive coefficients with p-values below 0.1% are shown with the daily sum of sentiments. On the other hand, with a similar level of significance, negative correlations are shown among MC and sentiments of disgust and fear. Moreover, Significant positive coefficients with p-values below 1% are shown with joyous and surprise sentiments. As expected, there are also significant direct and reverse correlations between overall positive and negative sentiments, respectively, and the MC.

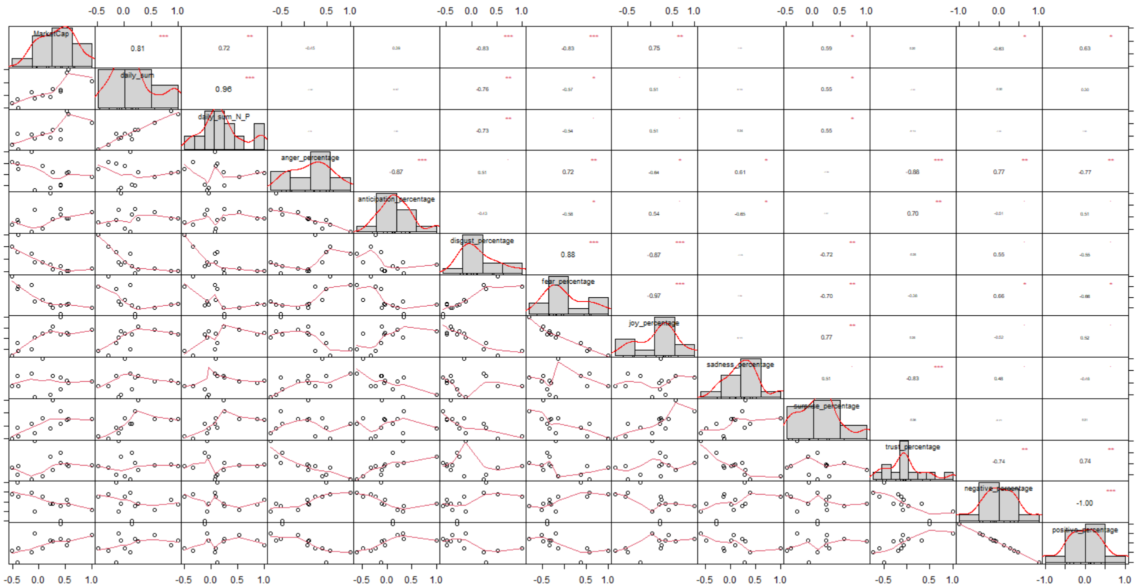

FIGURE 4-7- CORRELATION MATRIX: AZUKI- SCATTERPLOT, DATA SETS DISTRIBUTION HISTOGRAM AND P-VALUE

4.4.2.2 Sewer Pass

Sewer Pass, as demonstrated in Figure 4-8, seems to have the most significant correlations among different sentiments and the MCs. Significant positive coefficients with p-values below 0.1% are shown with the daily sum of sentiments. On the other hand, with a similar level of significance, positive and negative correlations are shown among MC and sentiments of joy and fear, respectively. Moreover, significant coefficients with p-values below 1% are shown with sadness and surprise sentiments.

As expected, there are also extremely significant direct and reverse correlations between overall positive and negative sentiments, respectively, and the MC.

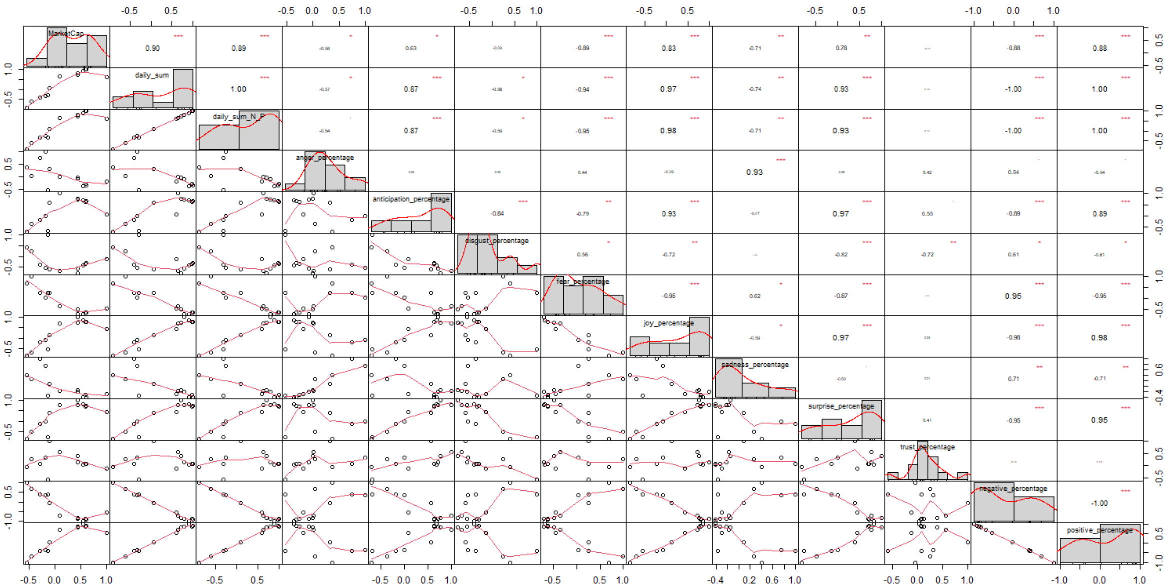

FIGURE 4-8- CORRELATION MATRIX: SEWER PASS- SCATTERPLOT, DATA SETS DISTRIBUTION HISTOGRAM AND P-VALUE

4.4.2.3 Axie Infinity

While 25 out of 2 NFTs showed at least a single significant correlation with at least on sentiments, Axie Infinity, as represented in Figure 4-9, showed no significant correlations between sentiments associated with it and MC fluctuations. Therefore, while an overall direction of the market could be induced, it’s not feasible to create a reliable correlation.

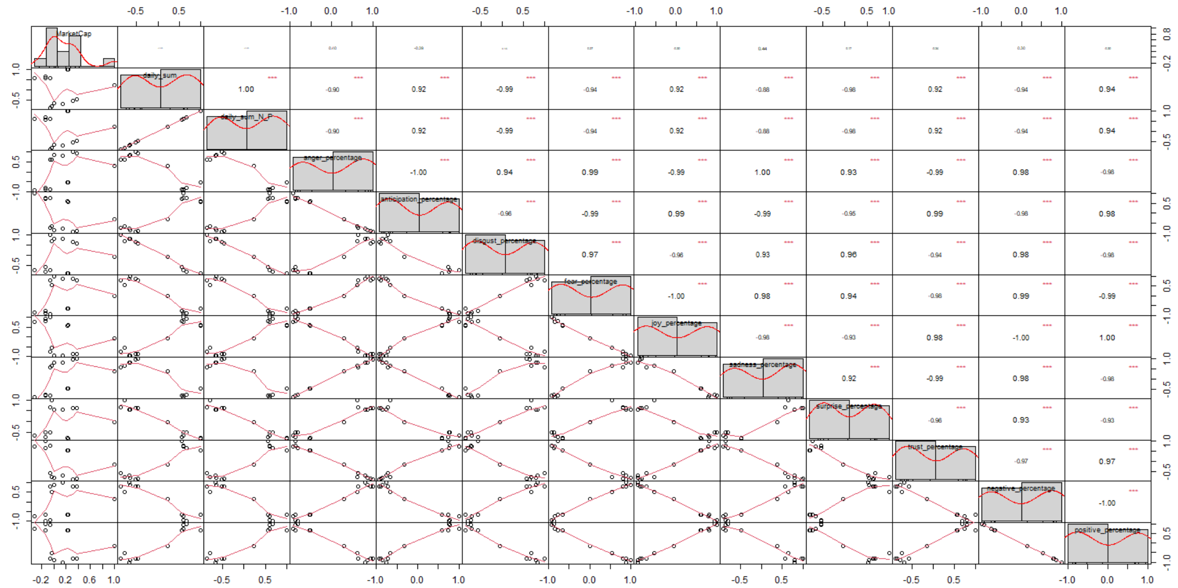

FIGURE 4-9- CORRELATION MATRIX: AXIE INFINITY- SCATTERPLOT, DATA SETS DISTRIBUTION HISTOGRAM AND P-VALUE

4.4.2.4 NBA Top Shot

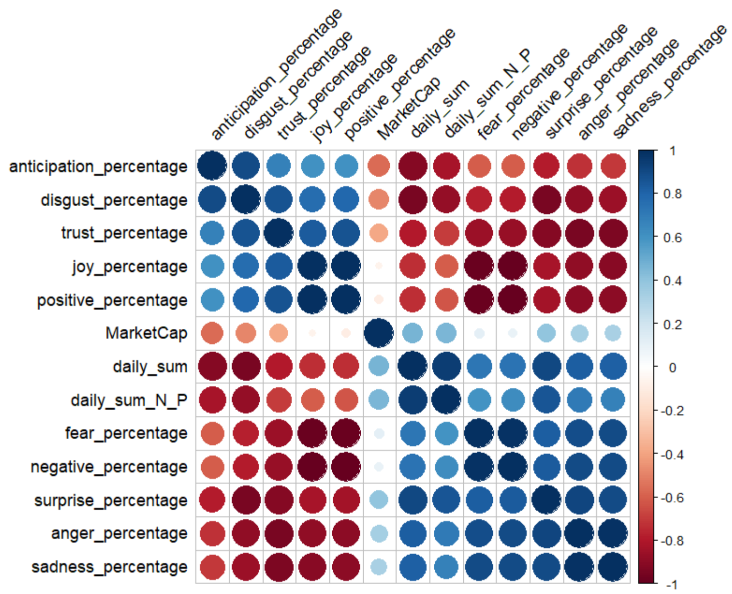

FIGURE 4-10- CORRELATION MATRIX: NBA TOP SHOT- SHOWING THE CORRELATION AMONG DIFFERENT SENTIMENTS AND MC

NBA Top Shot has exhibited the highest number of significant correlations with all extracted sentiments. As shown in Figures 4-10 and 4-11, there are significant correlations between MC and overall number of sentiments, anger, fear, sadness, surprise and overall negative sentiment. Reverse correlations exist with positive sentiments which are studied further in the end of this chapter.

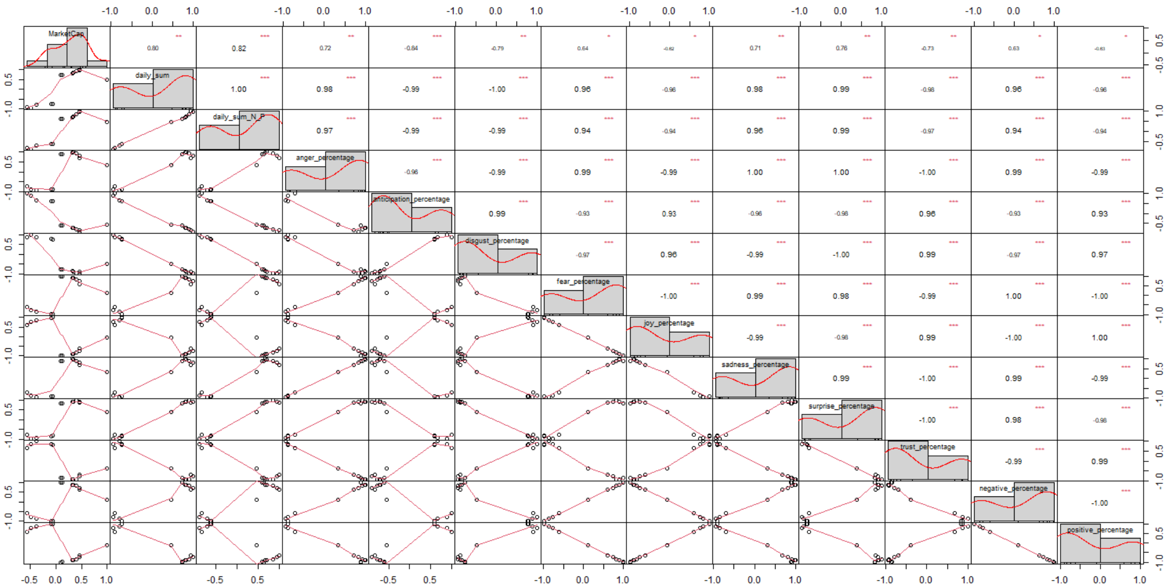

FIGURE 4-11- CORRELATION MATRIX: NBA TOP SHOT- SCATTERPLOT, DATA SETS DISTRIBUTION HISTOGRAM AND P-VALUE

4.4.2.5 Claynosaurz

The most notable correlation, in Figure 4-12, is the negative one between sentiments of disgust and the MC. It seems with the increase in disgust sentiments, the total value of trade decreases remarkably. Moreover, reverse correlations are identified between MC and other negative sentiments, including fear, sadness, anger and anticipation (a significant correlation with a p-value below 5%). Moreover, MC shows direct and indirect correlations, with overall positive and negative sentiments, respectively (a significant correlation with p-values below 1%).

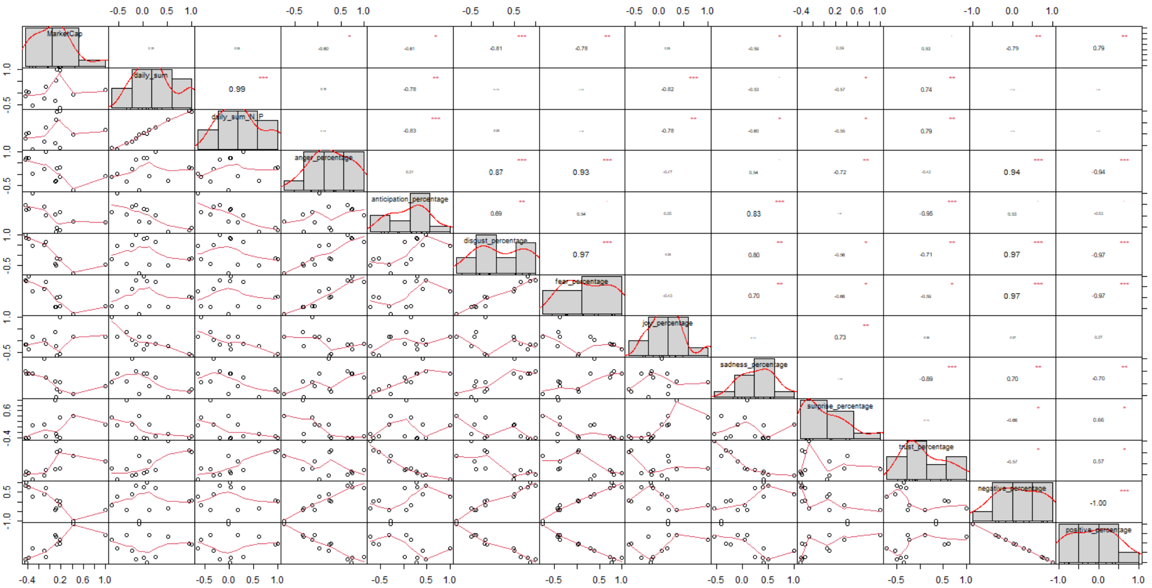

FIGURE 4-12- CORRELATION MATRIX: CLAYNOSAURZ- SCATTERPLOT, DATA SETS DISTRIBUTION HISTOGRAM AND P-VALUE

In conclusion, the data demonstrate that feelings conveyed in tweets may have a variety of effects on the MC of NFTs. While positive sentiments tend to correlate with increasing MC, negative emotions in tweets and anticipation often have inverse connections. These correlations may give useful information about the possible influence of public mood on NFT market prices. However, owing to the complexities of market dynamics, these correlations should be utilized in conjunction with other market indicators for a thorough analysis.

4.4.3 Discussing the significant correlations for varied NFT markets

Table 4-3 demonstrates the summary of the statistically significant sentiments regarding different correlations between MC and a variety of sentiments. Beginning with positive correlations, a rise in sentiment count (daily percentage of each sentiments) is connected with an increase in MC. This link implies that when users interact with a subject of NFT (expressing their views in the twitter), it might add to its market value. Notably, the NFTs 'Azuki' and 'Sewer Pass' have substantial positive connections in these attitudes. It's also worth mentioning that joy sensations are usually associated with higher MC.

Fear and disgust, on the contrary, are examples of emotions that often have negative associations. A perfect illustration of this pattern can be seen in 'Azuki,' where both fear and disgust have a significant detrimental impact on the MC. Disgust might be considered the antithesis of pleasure since it is always negatively associated with the MC.

Depending on the NFT, certain emotions, such as trust and anger, exhibit a mix of positive and negative correlations. For example, 'Decentraland' has a negative relationship between trust and MC, but 'Meebits' showed a positive relationship. Which could be explained through market overevaluation by the investors explained bellow.

In terms of NFTs with the highest and most significant level of correlations, Auki, Sewer Pass, NBA Top Shot, and Claynosaurz seem to be a great choice. Therefore, in the next section, these four NFTs will be further discussed in the next section in order to form a forecasting model. It should be noted that the overall count of sentiments, joy and disgust, having the highest level of correlation with MC, will also be incorporated to create the model.

TABLE 4-3- CORRELATIONS BETWEEN MC AND EXTRACTED SENTIMENTS FROM ASSOCIATED TWEETS

			Daily share of sentiments										
NFT	Chain	Category	Overall sentiments	Overall positive	Overall negative	Trust	Joy	Anticipation	Surprise	Fear	Disgust	Anger	Sadness
BAYC	Ethereum	PFPs	0.56	-	-	-	-	-	-	-	-	-	-
CryptoPunks	Ethereum	PFPs	-	-	-	-	-	-	-	-	-	-	-
MAYC	Ethereum	PFPs	-	-	-	-	0.54	-	-	-0.49	-	-	-
Azuki	Ethereum	PFPs	0.81	0.63	0.83	-	0.75	-	0.59	-0.83	-0.83	-	-
CloneX	Ethereum	PFPs	-	0.5	-0.5	-	-	-	-	-	-0.88	-	-
DeGods	Ethereum	PFPs	0.58	-	-	-	-	-	-	-	-	-	-
Meebits	Ethereum	PFPs	0.65	0.54	-0.54	0.56	0.67	-0.58	-	-	-	-0.58	-
Sewer Pass	Ethereum	PFPs	0.9	0.88	0.88	-	0.83	0.63	0.78	-0.89	-	-0.58	-0.71
Moonbirds	Ethereum	PFPs	-	-	-	-	0.49	-	-	-	-	-	-
The Captainz	Ethereum	PFPs	-	-	-	-0.65	0.51	-	-	-	-	-	-
Doodles	Ethereum	PFPs	0.56	-	-	-0.88	-	-0.59	-	-	-	-	0.67
Pudgy Penguins	Ethereum	PFPs	-	-	-	-	-	-0.5	-	-	-	-	-
VeeFriends	Ethereum	PFPs	-	-	-	-	-	-	-	-	-	0.48	-
CryptoNinja	Ethereum	PFPs	-	0.61	0.61	-	-	-	-	-0.53	-0.71	-	-0.6
Axie Infinity	Ethereum	Gaming	-	-	-	-	-	-	-	-	-	-	-
Decentraland	Ethereum	Virtual World	-	0.55	-0.55	-0.55	0.57	-	-	-	-	-	-
NBA Top Shot	Labs's Flow	-	0.8	-0.83	0.63	-0.73	-0.82	-0.84	0.76	0.64	-0.79	0.72	0.71
Rektguy	Ethereum	PFPs	-	-	-	-	-	-	-	-	-	-	-
Opepen	Ethereum	Art	0.56	-	-	-	0.59	-0.85	-	0.51	-	0.63	-
Claynosaurz	Solana	Art	-	0.79	-0.79	-	-	-0.61	-	-0.78	-0.81	-0.6	-0.59
Mocaverse	Ethereum	PFPs	-	-	-	-	-	-	-0.53	-	-	-	-
y00ts	Polygon	PFPs	-	-	-	-	-	-	-	-	-	-	-
DigiDaigaku	Ethereum	PFPs / Gaming	0.52	0.59	0.59	-0.87	0.56	-	-	-	-0.69	-0.5	-0.2
SchizoPosters	Ethereum	Art	0.8	-	-	-0.19	-	-	-	-	-	-	-
Holoself	Ethereum	Art/Gaming	-	-	-	0.55	-	-	-	-	-	-0.63	-
Mfers	Ethereum	PFPs	-	-	-	-	-	-	-	-	-	-	-
Ethlizards	Ethereum	PFPs	-	-	-	-	-	-	-	-	-	-	-

Color coding								
Significance at	0.10%	1.00%	5.00%	N.sgn	5.00%	1.00%	0.10%	

4.4.3.1 Unusual Correlations between Sentiments and Market Caps

As it is noted throughout the text, there are some peculiar correlations among extracted sentiment and MCs that might not be logical at first glance. The most noticeable ones were, 1) a decrease in market capitalization when sentiments of trust were increased, or 2) an increase in MC while sadness and anger were increasing. Moreover, NBA Top Shot NFT showed a reverse correlation between overall positive and negative sentiments with the MC.

Figure 4-13 represents a good example. This figure illustrates changes in the 0-1 transformed MC along with changes in daily trust sentiments percentage. A number of observations and probable explanations can be gleaned from the data and the points made earlier:

- *Speculation and overvaluation:* It appears that when trust sentiment is high (values such as 29.31, 29.98, 26.18, 25.36, and so on), the MC does not increase appropriately and sometimes even declines (for example, the MC is only 376 when trust sentiment is 29.31). This is consistent with the concept of market overreaction and correction. A boost in trust sentiment could have triggered a speculative buying frenzy, sending the NFT's price skyrocketing. When investors discover that the price has grown above the asset's intrinsic value, a correction may occur, resulting in a reduction in MC (Schnoering & Inzirillo, 2022).

- *Market maturity:* Despite generally steady trust sentiment in later stages (numbers such as 21.75, 21.81, 21.83, and so on), the MC exhibits large variations. This could indicate that the market is maturing. As the Captainz NFT market evolves, more information becomes available, and investors make judgments based not only on trust feeling, but also on a variety of other variables (Wang et al., 2022).
- *Risk perception and volatility:* The MC reveals substantial volatility in the middle of the data, when the trust percentage stays around the low 20s, with a range from 140,078 to 1,304,045. This could be a sign of a shift in risk perception. Because trust sentiment is low, it may imply a bigger risk, resulting in higher return expectations and greater volatility in the MC.
- *Additional external factors*: It is also possible that the abnormal association between trust sentiment and MC is influenced by other external factors that are not represented in this data. Independent of trust sentiment, factors like as overall market circumstances, news events relating to NFTs or Captainz in particular, regulatory changes, or technological developments can all have an impact on the MC (Wang et al., 2019).

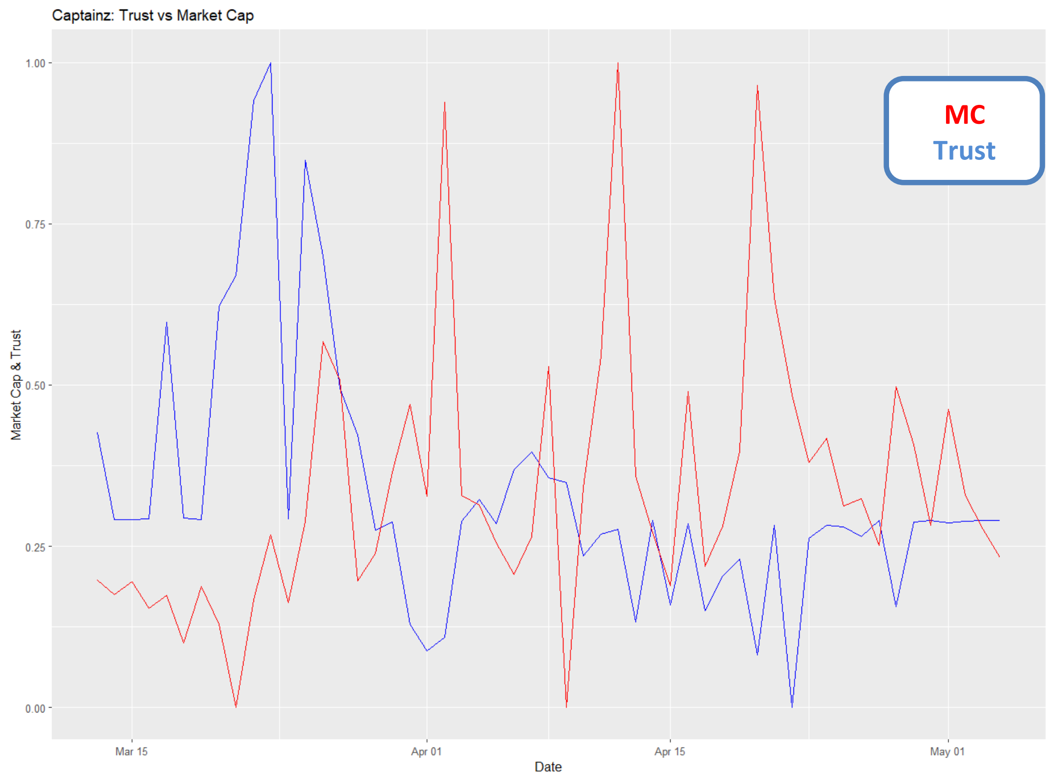

FIGURE 4-13 – CHANGES IN THE MC ALONG WITH VARIATION IN DAILY TRUST SENTIMENTS PERCENTAGE FOR CAPTAINZ NFT (NORMALIZED VALUES)

Furthermore, examining Figure 4-61 for NBA Top Shot, the anticipatory sentiment percentages and corresponding market capitalizations reveals some patterns that could explain the previously mentioned observation, namely, anticipation sentiment is generally associated with a drop in market capitalization for NFTs.

- *Market Volatility and Anticipation:* Due to the market's infancy, NBA Top Shot has experienced tremendous volatility. This volatility can be increased during times of heightened expectation, such as around pack drops or important events, resulting in market cap fluctuations (Ginsburg, 2022).

- *Pack Drops and Increased Supply:* New pack drops boost the market's supply of moments. If a moment becomes more common as a result of greater supply, its value may fall. This supply-demand dynamic may explain why there is a link between increased anticipation (which may be related with pack declines) and lower market capitalization (Lee, 2022).

- *Debut Excitement:* The debut of new packs usually generates a lot of excitement and drives higher pricing at first. However, after the excitement wears off and the most enthusiastic customers get what they want, prices frequently fall. As a result, a time of high anticipation may be followed by a decline in market capitalization as the initial euphoria wears off (Ginsburg, 2022; Lee, 2022).

- *Impact of Player Performance:* While outstanding performance by a player may generate short-term changes in the value of their related moments, it does not appear to have a long-term impact on market valuation. As a result, even moments of great expectation for notable games may not result in consistent gains in market value.

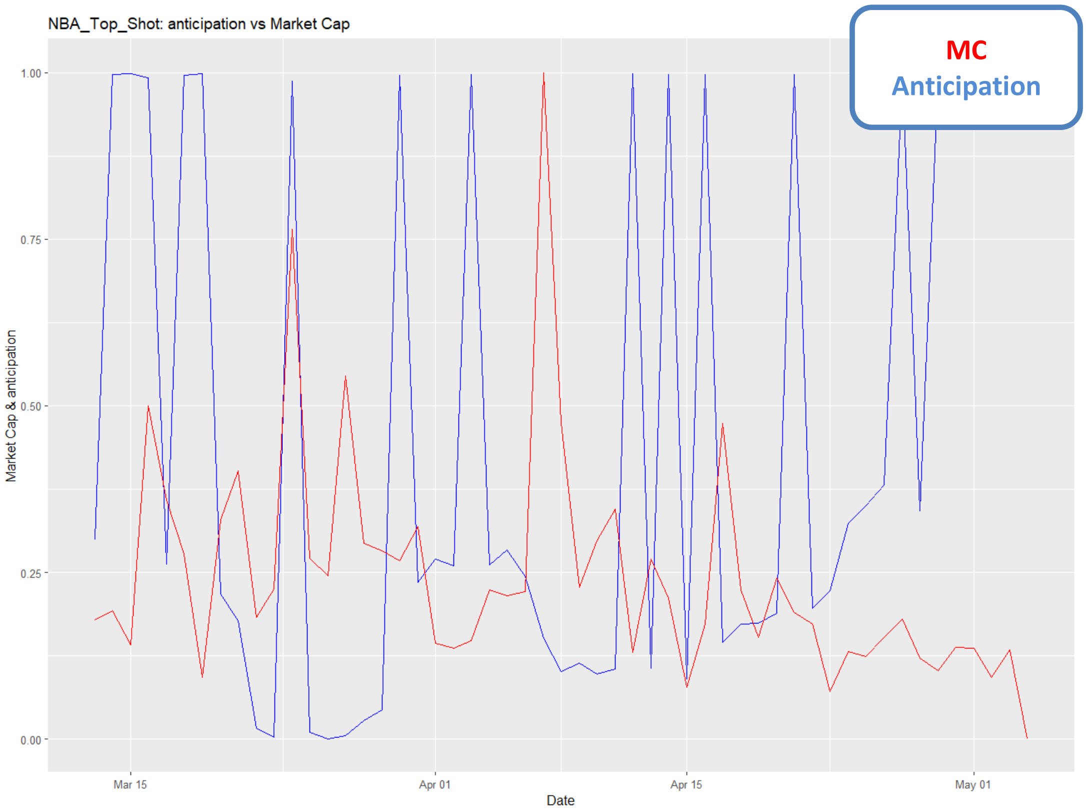

FIGURE 4-14 – CHANGES IN THE MC ALONG WITH VARIATION IN DAILY ANTICIPATION SENTIMENTS PERCENTAGE FOR NBA TOP SHOT NFT (NORMALIZED VALUES)

4.4.4 Development and validation of a predictive model

4.4.4.1 Development of the predictive model

Figure 4-62 gives an overview of trends of daily percentage share of selected sentiments in chosen NFTs and market capitalization. As it's demonstrated, the highest level of similarity can be demonstrated through Aziku, Claynosaurz, and NBA top shot. In other words, we will drop Swere Pass and move forward with the other three NFTs to create the predictive model.

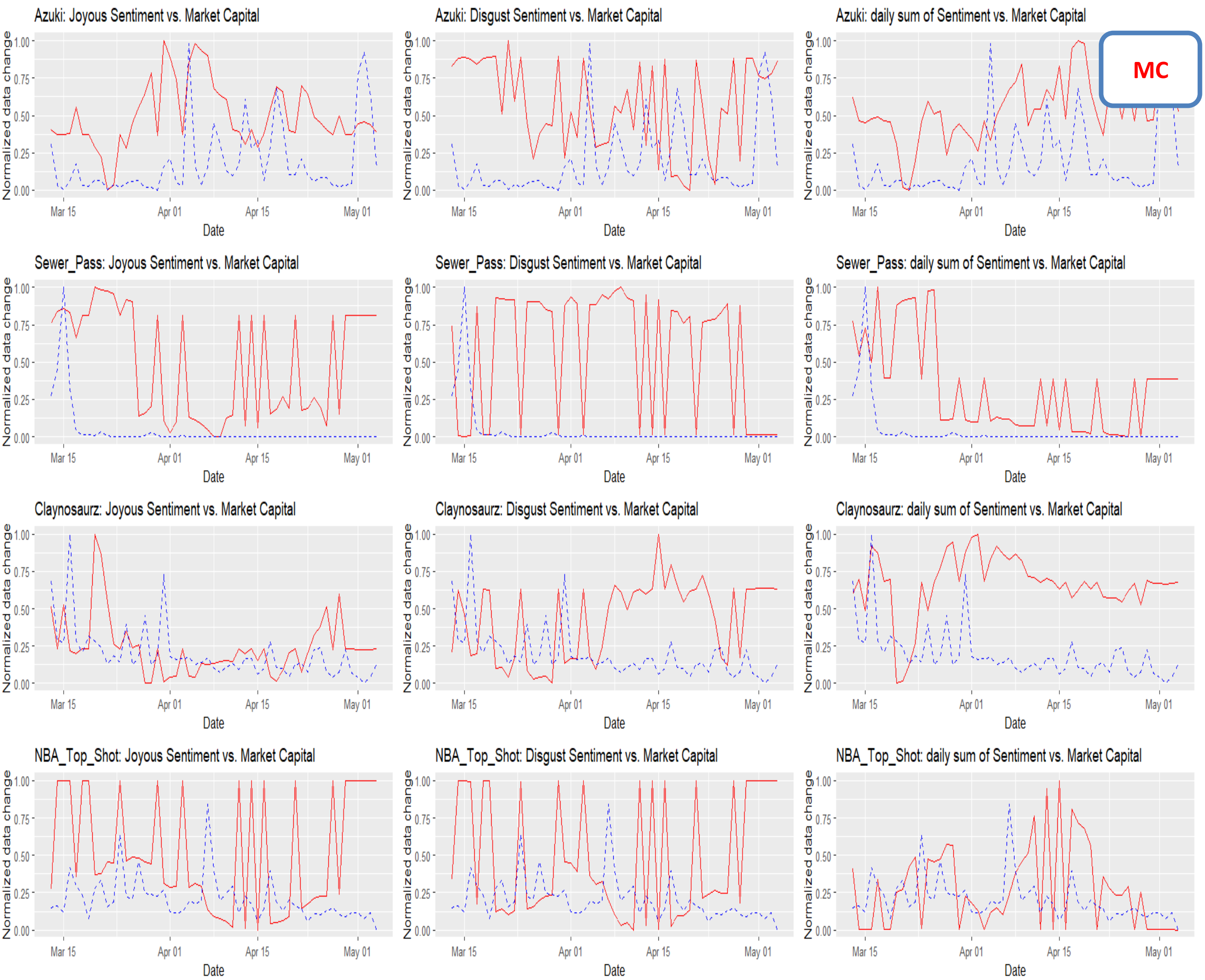

FIGURE 4-15 – TREND COMPARISON OF DAILY PERCENTAGE SHARE OF JOY, DISGUST AND SUM OF SENTIMENTS AND MARKET CAPITALIZATION (Normalized Values)

First of all, we are going to evaluate and discuss the Azuki NFT. Figure 4-63 shows the outcome of a Vector Autoregression (VAR) model used to examine the relationship between sentiment and market capitalization for Azuki NFT. The VAR model is a sort of time series model that represents the relationship between numerous time series variables using a system of equations. (Note: One has to make sure that the time series data is stationary before fitting a VAR model.)

The t-values and associated p-values indicate the statistical significance of each predictor. Specifically, the predictors disgust (Azuki_disgust_percentage_n.l1) and the daily sum of sentiments terms (Azuki_daily_sum_n.l1) are statistically significant at the 0.05 level, as their p-values are below 0.05. However, the other predictors, joy and historical market cap (lag of one day), are not statistically significant at the 0.05 level. Based on the model (p=2, the number of lags) has the highest p-value and correlation. In other words, we are using exclusively the data from the two days prior to make a forecast. However, as there was no difference in the final model (parameters with statistically significant impact), we did not bring it in the result section.

```
Azuki_MarketCap_n = Azuki_joy_percentage_n.l1 + Azuki_disgust_percentage_n.l1 + Azuki_daily_sum_n.l1 + Azuki_MarketCap_n.l1 + const

                             Estimate Std. Error t value Pr(>|t|)
Azuki_joy_percentage_n.l1      0.02942    0.15606   0.189   0.8513
Azuki_disgust_percentage_n.l1  0.25124    0.12313   2.041   0.0469 *
Azuki_daily_sum_n.l1           0.41636    0.17427   2.389   0.0209 *
Azuki_MarketCap_n.l1           0.23071    0.15025   1.535   0.1314
const                         -0.23985    0.16943  -1.416   0.1635
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 0.213 on 47 degrees of freedom
Multiple R-Squared: 0.2754,     Adjusted R-squared: 0.2137
F-statistic: 4.465 on 4 and 47 DF,  p-value: 0.003857
```

FIGURE 4-16 –VAR MODEL FOR AZUKI NFT

Figure 4-16 demonstrates the summary of the estimated VAR model, where `l1` refers to the first lag and `l2` to the second lag. The Pr(>|t|) column in this model represents the p-value related to the null hypothesis that the coefficient in question is equal to zero, indicating that it has no influence on the dependent variable.

For instance, `Azuki_disgust_percentage_n.l1` and `Azuki_daily_sum_n.l1` are statistically significant at the 5% level, as indicated by the single asterisk. Their p-values are below 0.05, suggesting strong evidence against the null hypothesis, so these variables significantly affect `Azuki_MarketCap_n`.

This means that the next day's normalized market capitalization of Azuki NFT can be predicted by the previous day's normalized disgust percentage and the normalized daily sum. The coefficients before each of these terms represent the expected change in `Azuki_MarketCap_n` for a one-unit increase in the corresponding predictor, assuming all other predictors are held constant.

Next, we went through the same procedure to create a similar predictive model for NBA Top Shot and Claynosaurz. Based on the VAR for NBA Top Shot (Figure 4-17), the lag of one day generated the closest fitting model (p-value=0.066).

```
Estimation results for equation NBA_Top_Shot_MarketCap_n:
=========================================================
NBA_Top_Shot_MarketCap_n = NBA_Top_Shot_joy_percentage_n.l1 + NBA_Top_Shot_disgust_percentage_n.l1 + NBA_Top_Shot_daily_sum_n.l1 + NBA_Top
_Shot_MarketCap_n.l1 + const

                                     Estimate Std. Error t value Pr(>|t|)
NBA_Top_Shot_joy_percentage_n.l1      0.33611    0.16294   2.063  0.04468 *
NBA_Top_Shot_disgust_percentage_n.l1 -0.43501    0.17557  -2.478  0.01687 *
NBA_Top_Shot_daily_sum_n.l1          -0.15698    0.12850  -1.222  0.22794
NBA_Top_Shot_MarketCap_n.l1           0.18794    0.13893   1.353  0.18259
const                                 0.24567    0.08501   2.890  0.00581 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 0.1385 on 47 degrees of freedom
Multiple R-Squared: 0.1672,     Adjusted R-squared: 0.09631
F-statistic: 2.359 on 4 and 47 DF,  p-value: 0.06693
```

FIGURE 4-17 - VAR MODEL FOR THE NBA TOP SHOT NFT

Moreover, based on the VAR for Claynosaurz (Figure 4-18), the lag of three days generated the closest fitting model (p-value=<0.001). Based on the results and focusing on the statistically significant coefficients ($p < 0.05$). Claynosaurz_MarketCap_n.l1 is the difference in Claynosaurz Market Cap from the previous day normalized. Claynosaurz_joy_percentage_n.l2 is the difference in the percentage of joy sentiment for Claynosaurz from two days ago normalized. And

Claynosaurz_MarketCap_n.l3 is the difference in Claynosaurz Market Cap from three days ago normalized.

```
Estimation results for equation Claynosaurz_MarketCap_n:
========================================================
Claynosaurz_MarketCap_n = Claynosaurz_joy_percentage_n.l1 + Claynosaurz_disgust_percentage_n.l1 + Claynosaurz
_daily_sum_n.l1 + Claynosaurz_MarketCap_n.l1 + Claynosaurz_joy_percentage_n.l2 + Claynosaurz_disgust_percenta
ge_n.l2 + Claynosaurz_daily_sum_n.l2 + Claynosaurz_MarketCap_n.l2 + Claynosaurz_joy_percentage_n.l3 + Claynos
aurz_disgust_percentage_n.l3 + Claynosaurz_daily_sum_n.l3 + Claynosaurz_MarketCap_n.l3 + const

                                    Estimate Std. Error t value Pr(>|t|)
Claynosaurz_joy_percentage_n.l1      0.50400    0.20001   2.520  0.01619 *
Claynosaurz_disgust_percentage_n.l1  0.20829    0.10225   2.037  0.04884 *
Claynosaurz_daily_sum_n.l1           0.14643    0.21069   0.695  0.49138
Claynosaurz_MarketCap_n.l1           0.41273    0.14684   2.811  0.00786 **
Claynosaurz_joy_percentage_n.l2     -0.78582    0.23202  -3.387  0.00169 **
Claynosaurz_disgust_percentage_n.l2 -0.15854    0.11284  -1.405  0.16837
Claynosaurz_daily_sum_n.l2          -0.41779    0.22553  -1.852  0.07195 .
Claynosaurz_MarketCap_n.l2          -0.05706    0.15204  -0.375  0.70956
Claynosaurz_joy_percentage_n.l3      0.30794    0.22125   1.392  0.17229
Claynosaurz_disgust_percentage_n.l3 -0.06773    0.10399  -0.651  0.51888
Claynosaurz_daily_sum_n.l3           0.15796    0.19653   0.804  0.42667
Claynosaurz_MarketCap_n.l3           0.37802    0.12041   3.140  0.00332 **
const                                0.11462    0.22525   0.509  0.61386
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 0.1283 on 37 degrees of freedom
Multiple R-Squared: 0.5611,     Adjusted R-squared: 0.4187
F-statistic: 3.942 on 12 and 37 DF,  p-value: 0.0006294
```

FIGURE 4-18 – VAR MODEL FOR THE Claynosaurz NFT

There is a difference in the number of lags between aforementioned NFTs; Azuki: 2 days, NFT Top Shot: 1 day, and Claynosaurz: 3 days. This indicated different behavior toward each of the NFTs and the level and volume of engagement. On another word, daily percentage of sentiments and market capitalization dating back to the last there days generates the most fitting model for Claynosaurz NFT compared to NBA Top Shot, where the most fitting model is generated using only a day before data. When looking at the average number of daily sentiments for each NFT (Claynosaurz: 1,420 sentiments extracted per day, Azuki: 1,600, NBA Top Shot: 2,548), it is clear that NBA Top Shot has the highest level of engagement, followed by Azuki and then Claynosaurz. This could be associated with the volatility of the market, leading to shorter lag periods for prediction modeling. Similarly, Figure 4-62 depicts the same conclusion.

4.4.4.2 Validation of the predictive model

A simple way to check the validity of the model is to use available data in terms of sentiments for each 3 NFTs and compare the resulting actual market cap with the calculated one based on the generated models. After performing such analysis, it was revealed that the generated models have pretty low accuracy showing significant variation from the actual value. This could be due to a range of reasons. One of the possible causes of this model's inaccuracy is its intrinsic assumptions. The model assumes that the relationships between variables are linear in nature and that mistakes are homoscedastically distributed, which means they have a constant variance. Furthermore, it is assumed that these errors have a normal distribution. When these assumptions are broken, the model's predictions can become inaccurate. For example, if the actual relationship among the variables is not linear, a linear model will fail to effectively represent this relationship, resulting in incorrect predictions.

A second cause is that the model's functional form may be erroneous. The accuracy of the model can be harmed if the functional form or arrangement of the model does not correspond to the genuine underlying process that creates the data. This could include cases where the model fails to account for relevant variables that have a major influence on the dependent variable or cases where improper variable transformations have been used.

Overfitting, a prevalent problem in predictive modeling, could be a third important explanation. If the model is overly complex, it may overfit to the oddities or noise in the training data. Overfitting essentially means that the model learns the exact characteristics and noise in the training data to the point where it significantly impairs the model's performance on new data. To put it another way, the model's parameters may be highly tuned in order to capture random noise or outliers in the training data, resulting in poor generalization capabilities when applied to unseen data. As a result, the model often performs well on training data but badly on test data or any new data, resulting in erroneous or illogical outputs.

Furthermore, the model's inaccuracy could be attributed to the inclusion of minor predictors. This could result in a more complex model than is necessary, contributing to more diversity in forecasts. Using an overly sophisticated model with too many predictors, especially those that do not contribute substantially to the outcome variable, might reduce the model's predictive power in many circumstances. This is due to the possibility that these unimportant predictors will inject excessive variation and noise into the model. Feature selection or feature reduction strategies, which try to choose the most appropriate predictors for the model, are frequent ways to reduce this problem. We may minimize the model's complexity, enhance its interpretability, and potentially raise its forecast performance by removing these minor predictors.

4.5 Conclusion

This chapter delves at the relationship between distinct sentiments and the market capitalization of a variety of Non-Fungible Tokens (NFTs). To visually portray these interactions across different NFTs, this chapter employs an array of correlation matrices.

One of the chapter's most important discoveries is the substantial association between market capitalization and joyful moods at p-values below 5%. This implies that an increase in joyful moods is associated with an increase in NFT market capitalization. This research highlights the potential impact of good mood on NFT's perceived value and subsequent market performance.

The chapter, on the other hand, indicates a considerable negative association between market capitalization and negative attitude. This suggests that a rise in negative sensations such as disgust, fear, sadness, anger, and anticipation is connected with a fall in NFT market capitalization. This negative correlation implies that unfavorable sentiments may have a negative impact on the market performance of NFTs.

Surprisingly, the chapter also discovers a negative relationship between market capitalization and trust attitudes. This somewhat unexpected conclusion implies that an increase in trust emotions leads to a fall in NFT market value. This study calls for more research into the underlying dynamics of trust emotions and market performance in the context of NFTs.

Finally, Chapter 4 gives a sophisticated explanation of the complicated relationship between various attitudes and NFT market capitalization. The findings highlight the significance of sentiment research in comprehending and forecasting market trends in the emerging field of NFTs.

5 CONCLUSION

5.1 Summary

The study set out to investigate the complex relationship between public mood as reflected on Twitter and the pricing dynamics of NFTs. The study was founded on the notion that sentiment expressed on social media platforms might have a major impact on NFT prices. The study used a systematic methodology that coupled sentiment analysis with financial data on NFTs to evaluate this notion.

The investigation started with a comprehensive keyword selection to ensure the relevance and specificity of the data obtained. The study extracted data mostly from Twitter, utilizing an academic-level API to obtain a vast number of data. To discover and classify sentiments in the collected data, sentiment analysis was performed using a well-established vocabulary. The financial data on NFTs was collected from a variety of platforms, offering critical insights into NFT market dynamics and pricing.

The data analysis employed a number of rigorous statistical methodologies to extract relevant and practical findings from the data, hence driving the study's objectives. The systematic and rigorous application of the R programming language for data administration and analysis aided this strategy. A mixture of statistical approaches was used, ranging from basic descriptive statistics to more advanced techniques including correlations, vector auto-regressive (VAR) models, and sentiment detection.

The study's findings verified the notion that there is a link between Twitter sentiment and NFT prices. The study discovered that joy and disgust have the strongest inverse connections with market capitalization. Furthermore, the overall number of sentiments is positively connected with market capitalization. The study also included the development and testing of time series models for market forecasting. The study provided a model for how the research was carried out, ensuring the research results' dependability and reproducibility.

5.2 Limitation of the study

Despite its achievements, it is critical to recognize the study's limits. For starters, the study mainly relied on Twitter data for sentiment analysis. While Twitter is a well-known and regularly utilized social media tool, it does not encompass all social media dialogue. Other platforms' views, such as Facebook, Instagram, Reddit, or specialist forums, may differ dramatically and provide further insights into the NFT market.

Second, the sentiment analysis was based solely on textual data and did not account for additional kinds of expression such as photos, videos, or graphics interchange formatted files, all of which are common in social media interactions. These modes of expression can convey significant mood and may have an impact on the NFT market. In addition, other sentiment approaches compared with the one used for the approach at hand, might reveal different results (Weismayer, 2021).

Next, the investigation was carried out over a limited time span. Because of the frequently changing nature of the NFT market, the study's conclusions may not be applicable to other time periods. As the market matures and new patterns emerge, the sentiment-NFT pricing relationship may shift.

Fourth, while the study concentrated on the relationship between social media mood and NFT prices, it did not establish a causal relationship. More research is needed to discover whether social media sentiment directly influences NFT prices or if other factors are at work.

Finally, while the study discovered correlations between various attitudes and NFT market capitalization, it should be highlighted that none of the correlations are significant for some specific NFTs. As a result, while an overall market direction can be generated, it is not possible to build a reliable correlation for all NFTs.

These constraints present opportunities for future research to build on the findings of this study and contribute to a better understanding of the NFT market.

5.3 Contribution to knowledge

In various aspects, the research has made substantial contributions to the current body of knowledge. For starters, it has shed light on the hitherto unknown influence of social media sentiment on the value of NFTs. Previous research has investigated the impact of social media sentiment on traditional financial markets; however, this study has extended this line of investigation to the developing field of NFTs.

The study demonstrated the use of sentiment analysis in predicting NFT prices. The research gave a novel viewpoint on the dynamics of the NFT market by adopting a systematic methodology that coupled sentiment analysis with financial data on NFTs. This methodological approach, which includes the extraction and analysis of a significant volume of Twitter data, could serve as a model for future studies on the topic.

Furthermore, the research has aided in clarifying the impact of different moods on the market capitalization of NFTs. The study discovered that joy and disgust attitudes had the most inverse connections with market value and that the overall number of sentiments is positively connected with market capitalization. These analyses have added to the knowledge of the relationship between public sentiment and financial markets.

5.4 Implications for relevant stakeholders

The findings of this study have broad implications for a varied range of stakeholders in the NFT industry. Understanding the impact of social media sentiment on NFT prices can help artists and producers navigate the market more effectively. They can use this information to strategically plan their releases, aligning them with positive sentiment patterns to optimize their potential market worth. They can also employ sentiment analysis to measure public reaction to their work and modify their strategy as needed.

The findings provide useful insights for investors and collectors that can help them make investment decisions. They may make more informed decisions about when to buy and sell NFTs if they understand the relationship between social media sentiment and NFT prices. This could result in higher returns on their investments.

The research provides information that platform developers and operators can utilize to improve the user experience on NFT platforms. Platforms, for example, may include sentiment analysis tools to give consumers with more information about the potential value of NFTs. This could help consumers make better judgments and become more engaged with the site.

The study gives up new options for additional research in the fields of sentiment analysis and NFT price prediction for researchers and academics. The research approach and conclusions can be used as a foundation for future investigations, advancing knowledge in this sector.

5.5 Future research

The study indicated numerous potential future research paths. These are some examples:

Connection between how people feel on social media and the prices of NFT artwork: The current study has found a connection between how people feel on social media and the prices of NFT artwork in general. Future studies could explore deeper into this association by concentrating on NFT artwork prices in particular. This may entail examining the emotion surrounding individual pieces of NFT artwork and assessing how that sentiment affects their market value.

Impact of influencer endorsements and online community activity on price fluctuations: The study revealed the impact of social media sentiment on NFT prices. Future research should look into other types of social media activity, including influencer endorsements and online community involvement, and their impact on NFT price swings.

Incorporation of multi-modal data: For sentiment analysis, the study mostly relied on textual data from Twitter. To acquire a better knowledge of the elements that drive NFT values, future study should look at including multi-modal data, such as visual qualities of NFT artwork or audio data from podcasts and interviews.

Application of sentiment analysis techniques to the NFT art market: As the field of NFTs expands, there will undoubtedly be an increasing stake in applying sentiment analysis techniques to the NFT art market. Future studies could investigate this potential application and help to develop more advanced algorithms for predicting NFT art prices.

Finally, the current study has opened up a new research route in the field of sentiment analysis and NFT price prediction. The prospective future research directions identified in this study may contribute to the advancement of this field.

6 BIBLIOGRAPHY

About CoinGecko. (2023). In *CoinGecko*. https://www.coingecko.com/en/about

Abreu, P. W., Aparicio, M., & Costa, C. J. (2018). Blockchain technology in the auditing environment. *2018 13th Iberian Conference on Information Systems and Technologies (CISTI)*, 1–6.

Academy, B. (2022). Binance Academy 2021 Year in Review. *Binance Academy*. https://academy.binance.com/en/articles/binance-academy-2021-year-in-review

Adhami, S., Giudici, G., & Martinazzi, S. (2018). Why do businesses go crypto? An empirical analysis of initial coin offerings. *Journal of Economics and Business*, *100*, 64–75.

Aggarwal, C. C., & Zhai, C. (2012). A survey of text classification algorithms. *Mining Text Data*, 163–222.

Aggarwal, S., & Kumar, N. (2021). Chapter Twelve - Cryptocurrencies. In S. Aggarwal, N. Kumar, & P. B. T.-A. in C. Raj (Eds.), *The Blockchain Technology for Secure and Smart Applications across Industry Verticals* (Vol. 121, pp. 227–266). Elsevier. https://doi.org/https://doi.org/10.1016/bs.adcom.2020.08.012

Ahmet, E. F. E. (n.d.). Taking Virtual Reality and Augmented Reality to The Next Level: Artificial Intelligence with Mixed Reality. *Kamu Yönetimi ve Teknoloji Dergisi*, *4*(2), 141–165.

Ali, O., Momin, M., Shrestha, A., Das, R., Alhajj, F., & Dwivedi, Y. K. (2023). A review of the key challenges of non-fungible tokens. *Technological Forecasting and Social Change*, *187*, 122248.

Androulaki, E., Barger, A., Bortnikov, V., Cachin, C., Christidis, K., De Caro, A., Enyeart, D., Ferris, C., Laventman, G., & Manevich, Y. (2018). Hyperledger fabric: a distributed operating system for permissioned blockchains. *Proceedings of the Thirteenth EuroSys Conference*, 1–15.

Ante, L. (2022). The non-fungible token (NFT) market and its relationship with Bitcoin and Ethereum. *FinTech*, *1*(3), 216–224.

Async: Create Art and Music NFTs. (2023). https://async.art

Azaria, A., Ekblaw, A., Vieira, T., & Lippman, A. (2016). Medrec: Using blockchain for medical data access and permission management. *2016 2nd International Conference on Open and Big Data (OBD)*, 25–30.

Bamakan, S. M. H., Nezhadsistani, N., Bodaghi, O., & Qu, Q. (2021). *A decentralized framework for patents and intellectual property as nft in blockchain networks*.

Banerjee, I., Ling, Y., Chen, M. C., Hasan, S. A., Langlotz, C. P., Moradzadeh, N., Chapman, B., Amrhein, T., Mong, D., & Rubin, D. L. (2019). Comparative effectiveness of convolutional neural network (CNN) and recurrent neural network (RNN) architectures for radiology text report classification. *Artificial Intelligence in Medicine*, *97*, 79–88.

Bao, H., & Roubaud, D. (2021). Recent development in fintech: Non-fungible token. In *FinTech* (Vol. 1, Issue 1, pp. 44–46). MDPI.

Baudier, P., Kondrateva, G., Ammi, C., & Seulliet, E. (2021). Peace engineering: The contribution of blockchain systems to the e-voting process. *Technological Forecasting and Social Change*, *162*, 120397.

Baur, D. G., Dimpfl, T., & Kuck, K. (2018). Bitcoin, gold and the US dollar–A replication and extension. *Finance Research Letters*, *25*, 103–110.

Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of exchange or speculative assets? *Journal of International Financial Markets, Institutions and Money*, *54*, 177–189.

Bhardwaj, E., Samanta, G., & Fancy, C. (2023). An NFT marketplace with predictive and analytical modeling on the industry trends and growth to visualize and recommend creators and NFTs with uprising value potential. *2023 International Conference on Networking and Communications (ICNWC)*, 1–5.

Bird, S., Klein, E., & Loper, E. (2009). *Natural language processing with Python: analyzing text* *with the natural language toolkit*. " O'Reilly Media, Inc."

Birjali, M., Kasri, M., & Beni-Hssane, A. (2021). A comprehensive survey on sentiment analysis: Approaches, challenges and trends. *Knowledge-Based Systems*, *226*, 107134. https://doi.org/https://doi.org/10.1016/j.knosys.2021.107134

Bland, R. (2022). The State Tax Conundrum Of Cryptocurrency? *Forbes*. https://www.forbes.com/sites/taxnotes/2022/04/04/the-state-tax-conundrum-of-cryptocurrency

Böhme, R., Christin, N., Edelman, B., & Moore, T. (2015). Bitcoin: Economics, technology, and governance. *Journal of Economic Perspectives*, *29*(2), 213–238.

Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science*, *2*(1), 1–8.

Bonneau, J., Miller, A., Clark, J., Narayanan, A., Kroll, J. A., & Felten, E. W. (2015). Sok: Research perspectives and challenges for bitcoin and cryptocurrencies. *2015 IEEE Symposium on Security and Privacy*, 104–121.

Brown, R. G., Carlyle, J., Grigg, I., & Hearn, M. (2016). Corda: an introduction. *R3 CEV, August*, *1*(15), 14.

Build whats next with the new twitter developer platform. (2023). https://developer.twitter.com/en/blog/product-news/2021/build-whats-next-with-the-new-twitter-developer-platform

Bukovina, J. (2016). Social media big data and capital markets—An overview. *Journal of Behavioral and Experimental Finance*, *11*, 18–26.

Buterin, V., & Griffith, V. (2017). Casper the friendly finality gadget. *ArXiv Preprint ArXiv:1710.09437*.

Caxton, S. V. M., Naveen, K., Karthik, R., & Bama, S. S. (2022). User-Centered Evaluation and Design Suggestions for NFT Marketplaces. *2022 International Conference on Inventive Computation Technologies (ICICT)*, 1214–1221.

Chen, C.-C., Huang, H.-H., & Chen, H.-H. (2020). NLP in FinTech applications: past, present and future. *ArXiv Preprint ArXiv:2005.01320*.

Chen, H., De, P., Hu, Y. J., & Hwang, B.-H. (2013). *Customers as advisors: The role of social media in financial markets*. Working paper.

Chohan, U. W. (2021). Non-fungible tokens: Blockchains, scarcity, and value. *Critical Blockchain Research Initiative (CBRI) Working Papers*.

Clayman, S. E., & Reisner, A. (1998). Gatekeeping in action: Editorial conferences and assessments of newsworthiness. *American Sociological Review*, 178–199.

CoinMarketCap. (2023). 2023 NFT Market Analysis: An Insider Look. *CoinMarketCap Alexandria*. https://coinmarketcap.com/alexandria/article/2023-nft-market-analysis:-an-insider-look

CryptoKitties. (2023). CryptoKitties | Collect and breed digital cats! In *CryptoKitties*. https://www.cryptokitties.co

CryptoSlam! NFT data, rankings, prices, sales volume charts, market cap. (2023). https://www.cryptoslam.io

D'Onfro, D. (2021). Error-Resilient Consumer Contracts. *Duke LJ*, *71*, 541.

Dowling, M. (2022). Is non-fungible token pricing driven by cryptocurrencies? *Finance Research Letters*, *44*, 102097.

Dumitriu, A., May, A., Velios, A., Sakki, Z., Korakidou, V., Marçal, H., & Panagiaris, G. (2021). Unruly objects: NFTs, blockchain technologies and bio-conservation. *Technoetic Arts: A Journal of Speculative Research*, *19*(3), 383–397.

Dylan-Ennis, P., Kavanagh, D., & Araujo, L. (2023). The dynamic imaginaries of the Ethereum project. *Economy and Society*, 1–23.

Ekblaw, A., Azaria, A., Halamka, J. D., & Lippman, A. (2016). A Case Study for Blockchain in Healthcare:"MedRec" prototype for electronic health records and medical research data. *Proceedings of IEEE Open & Big Data Conference*, *13*, 13.

Ertürk, E., Doğan, M., Kadiroğlu, Ü., & Karaarslan, E. (2021). NFT based fundraising system for preserving cultural heritage: heirloom. *2021 6th International Conference on Computer Science and Engineering (UBMK)*, 699–702.

Et John, R. (2021). #164 | Room spéciale NFT & Cinema avec Me Ingrid Haziot et Margaux Fournier. *NFT Morning*. https://www.nftmorning.com/p/164-nft-et-cinema#details

Ethereum Improvement Proposals. (2023). In *Ethereum Improvement Proposals*. https://eips.ethereum.org/EIPS/eip-721

Eyal, I., & Sirer, E. G. (2018). Majority is not enough: Bitcoin mining is vulnerable. *Communications of the ACM*, *61*(7), 95–102.

Fiedler, I., & Ante, L. (2023). Stablecoins. In *The Emerald Handbook on Cryptoassets: Investment Opportunities and Challenges* (pp. 93–105). Emerald Publishing Limited.

Getting Started with the Twitter API. (2023). https://developer.twitter.com/en/docs/twitter-api/getting-started/about-twitter-api

Ginsburg, R. (2022). The Impressive Rise and Untimely Fall of NBA Top Shot. *Nft Now*. https://nftnow.com/features/what-happened-to-nba-top-shot

Giudici, P., & Abu-Hashish, I. (2019). What determines bitcoin exchange prices? A network VAR approach. *Finance Research Letters*, *28*, 309–318.

Grand View Research, I. (2023). Non-fungible Token Market to Reach $211.72 Billion by 2030: Grand View Research, Inc. *PR Newswire*. https://www.prnewswire.com/news-releases/non-fungible-token-market-to-reach-211-72-billion-by-2030-grand-view-research-inc-301842161.html

Guo, R., Shi, H., Zhao, Q., & Zheng, D. (2018). Secure attribute-based signature scheme with multiple authorities for blockchain in electronic health records systems. *IEEE Access*, *6*, 11676–11686.

Guo, W. (2022). For Today's Carbon Tracking, Carbon Credit Environmental Protection NFT Application. *Carbon Credit Environmental Protection NFT Application (March 14, 2022)*.

Harz, D., & Knottenbelt, W. (2018). Towards safer smart contracts: A survey of languages and verification methods. *ArXiv Preprint ArXiv:1809.09805*.

Herian, R., Di Bernardino, C., Chomczyk Penedo, A., Ellul, J., Ferreira, A., von Goldbeck, A., Siadat, A., & Siedler, N.-L. (2021). *NFT–Legal Token Classification*.

Hirsh, J. B., & Peterson, J. B. (2009). Personality and language use in self-narratives. *Journal of Research in Personality*, *43*(3), 524–527.

Jain, S., Bruckmann, C., & McDougall, C. (2022). NFT Appraisal Prediction: Utilizing Search Trends, Public Market Data, Linear Regression and Recurrent Neural Networks. *ArXiv Preprint ArXiv:2204.12932*.

Jansen, B. J., Zhang, M., Sobel, K., & Chowdury, A. (2009). Twitter power: Tweets as electronic word of mouth. *Journal of the American Society for Information Science and Technology*, *60*(11), 2169–2188.

Johnson, A., & are NFT, W. T. F. (2022). *WTF are NFTs, Smart Contracts, and Tokens? How Blockchain Tech Disrupts the Music Industry to Empower Artists*.

Johri, P., Khatri, S. K., Al-Taani, A. T., Sabharwal, M., Suvanov, S., & Kumar, A. (2021). Natural language processing: History, evolution, application, and future work. *Proceedings of 3rd International Conference on Computing Informatics and Networks: ICCIN 2020*, 365–375.

Jones, K. S. (1994). Natural language processing: a historical review. *Current Issues in Computational Linguistics: In Honour of Don Walker*, 3–16.

Joy, A., Zhu, Y., Peña, C., & Brouard, M. (2022). Digital future of luxury brands: Metaverse, digital fashion, and non-fungible tokens. *Strategic Change*, *31*(3), 337–343.

Juels, A., Kosba, A., & Shi, E. (2016). The ring of gyges: Investigating the future of criminal smart contracts. *Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security*, 283–295.

KABORE, K. M. (2018). *Developing machine learning methods for business intelligence*. Abdullah Gül Üniversitesi.

Kaczynski, S., & Kominers, S. D. (2021). How NFTs create value. *Harvard Business Review*, *10*.

Kamath, R. (2018). Food traceability on blockchain: Walmart's pork and mango pilots with IBM. *The Journal of the British Blockchain Association*, *1*(1).

Kaplanov, N. (2012). Nerdy money: Bitcoin, the private digital currency, and the case against its regulation. *Loy. Consumer L. Rev.*, *25*, 111.

Kapoor, A., Guhathakurta, D., Mathur, M., Yadav, R., Gupta, M., & Kumaraguru, P. (2022). Tweetboost: Influence of social media on nft valuation. *Companion Proceedings of the Web Conference 2022*, 621–629.

Kaur, A., & Gupta, V. (2013). A survey on sentiment analysis and opinion mining techniques. *Journal of Emerging Technologies in Web Intelligence*, *5*(4), 367–371.

Kirilenko, A. P., & Stepchenkova, S. O. (2014). Public microblogging on climate change: One year of Twitter worldwide. *Global Environmental Change*, *26*, 171–182.

Kraaijeveld, O., & De Smedt, J. (2020). The predictive power of public Twitter sentiment for forecasting cryptocurrency prices. *Journal of International Financial Markets, Institutions and Money*, *65*, 101188. https://doi.org/https://doi.org/10.1016/j.intfin.2020.101188

Kralj Novak, P., Smailović, J., Sluban, B., & Mozetič, I. (2015). Sentiment of emojis. *PloS One*, *10*(12), e0144296.

Kshetri, N., & Voas, J. (2018). Blockchain in developing countries. *It Professional*, *20*(2), 11–14.

Kwon, J.-H., & Tae, J.-H. (2022). NFT Contents Enjoyment and Policy Suggestions-Focusing on Digital Aura Concept. 한국엔터테인먼트산업학회논문지, *16*(5), 155–171.

Lamon, C., Nielsen, E., & Redondo, E. (2017). Cryptocurrency price prediction using news and social media sentiment. *SMU Data Sci. Rev*, *1*(3), 1–22.

Lazuashvili, N. (2019). Integration of the blockchain technology into the land registration system. *A Case Study of Georgia. PhD Thesis*, *5*.

Lee, Y. (2022). Measuring the impact of rarity on price: Evidence from NBA top shot. *Marketing Letters*, *33*(3), 485–498.

Ligthart, A., Catal, C., & Tekinerdogan, B. (2021). Systematic reviews in sentiment analysis: a tertiary study. *Artificial Intelligence Review*, 1–57.

Medagoda, N., & Shanmuganathan, S. (2015). Keywords based temporal sentiment analysis. *2015 12th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD)*, 1418–1425.

Medhat, W., Hassan, A., & Korashy, H. (2014). Sentiment analysis algorithms and applications: A survey. *Ain Shams Engineering Journal*, *5*(4), 1093–1113. https://doi.org/https://doi.org/10.1016/j.asej.2014.04.011

MetaversePost on Binance Feed: Pudgy Penguins Makes Bigger IP Play With $9M Raise in Seed Round Led By 1kx | Binance Feed. (2023). In *Binance Feed*. https://www.binance.com/fr/feed/post/505683

Meyer, E., Welpe, I. M., & Sandner, P. G. (2022). *Decentralized finance—A systematic literature review and research directions*.

Meyns, S. C. A. (2022). *Happy, risky assets: Uncertainty and (mis) trust in non-fungible token (NFT) conversations on Twitter*.

Mielke, S. J., Alyafeai, Z., Salesky, E., Raffel, C., Dey, M., Gallé, M., Raja, A., Si, C., Lee, W. Y., & Sagot, B. (2021). Between words and characters: A brief history of open-vocabulary modeling and tokenization in NLP. *ArXiv Preprint ArXiv:2112.10508*.

Miers, I., Garman, C., Green, M., & Rubin, A. D. (2013). Zerocoin: Anonymous distributed e-cash from bitcoin. *2013 IEEE Symposium on Security and Privacy*, 397–411.

Mohammad, S. M., & Turney, P. D. (2013). Nrc emotion lexicon. *National Research Council, Canada*, *2*, 234.

Moraes, R., Valiati, J. F., & Neto, W. P. G. (2013). Document-level sentiment classification: An empirical comparison between SVM and ANN. *Expert Systems with Applications*, *40*(2), 621–633.

Nadini, M., Alessandretti, L., Di Giacinto, F., Martino, M., Aiello, L. M., & Baronchelli, A. (2021).

Mapping the NFT revolution: market trends, trade networks, and visual features. *Scientific Reports*, *11*(1), 1–11.

Nadkarni, P. M., Ohno-Machado, L., & Chapman, W. W. (2011). Natural language processing: an introduction. *Journal of the American Medical Informatics Association*, *18*(5), 544–551.

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system. *Decentralized Business Review*, 21260.

Nankani, H., Dutta, H., Shrivastava, H., Rama Krishna, P., Mahata, D., & Shah, R. R. (2020). Multilingual sentiment analysis. *Deep Learning-Based Approaches for Sentiment Analysis*, 193–236.

Narayanan, A., & Möser, M. (2017). Obfuscation in bitcoin: Techniques and politics. *ArXiv Preprint ArXiv:1706.05432*.

Nofer, M., Gomber, P., Hinz, O., & Schiereck, D. (2017). Blockchain. *Business & Information Systems Engineering*, *59*, 183–187.

O'Connor, B., Balasubramanyan, R., Routledge, B., & Smith, N. (2010). From tweets to polls: Linking text sentiment to public opinion time series. *Proceedings of the International AAAI Conference on Web and Social Media*, *4*(1), 122–129.

O'Dwyer, K. J., & Malone, D. (2014). *Bitcoin mining and its energy footprint*.

Ohk, L., Au, C.-D., & Zureck, A. (2021). *Digital Currencies in Economies-Critical Analysis on the Future Role*.

Omohundro, S. (2014). Cryptocurrencies, smart contracts, and artificial intelligence. *AI Matters*, *1*(2), 19–21.

Ortigosa-Hernández, J., Rodríguez, J. D., Alzate, L., Lucania, M., Inza, I., & Lozano, J. A. (2012). Approaching sentiment analysis by using semi-supervised learning of multi-dimensional classifiers. *Neurocomputing*, *92*, 98–115.

Pak, A., & Paroubek, P. (2010). Twitter as a corpus for sentiment analysis and opinion mining. *LREc*, *10*(2010), 1320–1326.

Pang, B., & Lee, L. (2004). A sentimental education: Sentiment analysis using subjectivity summarization based on minimum cuts. *ArXiv Preprint Cs/0409058*.

Pang, B., Lee, L., & Vaithyanathan, S. (2002). Thumbs up? Sentiment classification using machine learning techniques. *ArXiv Preprint Cs/0205070*.

Pano, T., & Kashef, R. (2020). A Complete VADER-Based Sentiment Analysis of Bitcoin (BTC) Tweets during the Era of COVID-19. *Big Data and Cognitive Computing*, *4*(4), 33. https://doi.org/10.3390/bdcc4040033

Parry, M. T. (2019). *Predicting the direction of stock price movements from historical data and sentiment analysis of Tweets*.

Paul, M., & Dredze, M. (2011). You are what you tweet: Analyzing twitter for public health. *Proceedings of the International AAAI Conference on Web and Social Media*, *5*(1), 265–272.

Pelechrinis, K., Liu, X., Krishnamurthy, P., & Babay, A. (2022). Spotting anomalous trades in NFT markets: The case of NBA TopShot. *ArXiv Preprint ArXiv:2202.04013*.

Pinto-Gutiérrez, C., Gaitán, S., Jaramillo, D., & Velasquez, S. (2022). The NFT hype: what draws attention to non-fungible tokens? *Mathematics*, *10*(3), 335.

Poon, J., & Dryja, T. (2016). *The bitcoin lightning network: Scalable off-chain instant payments*.

Reddy, N. N., Naresh, E., & BP, V. K. (2020). Predicting stock price using sentimental analysis through twitter data. *2020 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT)*, 1–5.

Regner, F., Urbach, N., & Schweizer, A. (2019). *NFTs in practice–non-fungible tokens as core component of a blockchain-based event ticketing application*.

Rella, L. (2019). Blockchain technologies and remittances: from financial inclusion to correspondent banking. *Frontiers in Blockchain*, *2*, 14.

Russell, F. (2022). NFTs and value. *M/C Journal*, *25*(2).

Sadia, A., Khan, F., & Bashir, F. (2018). An overview of lexicon-based approach for sentiment analysis. *2018 3rd International Electrical Engineering Conference (IEEC 2018)*, 1–6.

Sagnika, S., Pattanaik, A., Mishra, B. S. P., & Meher, S. K. (2020). A review on multi-lingual sentiment analysis by machine learning methods. *Journal of Engineering Science and Technology Review*, *13*(2), 154.

Sattarov, O., Jeon, H. S., Oh, R., & Lee, J. D. (2020). Forecasting bitcoin price fluctuation by twitter sentiment analysis. *2020 International Conference on Information Science and Communications Technologies (ICISCT)*, 1–4.

Schnoering, H., & Inzirillo, H. (2022). Constructing a NFT price index and applications. *ArXiv Preprint ArXiv:2202.08966*.

Schober, P., Boer, C., & Schwarte, L. A. (2018). Correlation Coefficients: Appropriate Use and Interpretation. *Anesthesia and Analgesia*, *126*(5), 1763–1768. https://doi.org/10.1213/ANE.0000000000002864

Scholand, A. J., Tausczik, Y. R., & Pennebaker, J. W. (2010). Social language network analysis. *Proceedings of the 2010 ACM Conference on Computer Supported Cooperative Work*, 23–26.

Shahzad, S. J. H., Anas, M., & Bouri, E. (2022). Price explosiveness in cryptocurrencies and Elon Musk's tweets. *Finance Research Letters*, *47*, 102695.

Sharma, P., Sahoo, A. R., Sinha, S., & Bharadwaj, S. (2022). *NFT artwork generation using oscillatory activation functions in GANs*.

Sohail, S. S., Khan, M. M., Arsalan, M., Khan, A., Siddiqui, J., Hasan, S. H., & Alam, M. A. (2021). Crawling Twitter data through API: A technical/legal perspective. *ArXiv Preprint ArXiv:2105.10724*.

Stavroyiannis, S., & Babalos, V. (2019). Herding behavior in cryptocurrencies revisited: Novel evidence from a TVP model. *Journal of Behavioral and Experimental Finance*, *22*, 57–63.

Swan, M. (2017). Anticipating the economic benefits of blockchain. *Technology Innovation Management Review*, *7*(10), 6–13.

Swan, M. (2018). Blockchain for business: Next-generation enterprise artificial intelligence systems. In *Advances in computers* (Vol. 111, pp. 121–162). Elsevier.

Taboada, M. (2016). Sentiment analysis: An overview from linguistics. *Annual Review of Linguistics*, *2*, 325–347.

Tapscott, D., & Tapscott, A. (2016). *Blockchain revolution: how the technology behind bitcoin is changing money, business, and the world*. Penguin.

Tech, N. (2023). A Deep-Dive on NFT Marketplaces. *NFT Technologies Inc.* https://www.nfttech.com/newsroom/a-deep-dive-on-nft-marketplaces

Tenney, I., Xia, P., Chen, B., Wang, A., Poliak, A., McCoy, R. T., Kim, N., Van Durme, B., Bowman, S. R., & Das, D. (2019). What do you learn from context? probing for sentence structure in contextualized word representations. *ArXiv Preprint ArXiv:1905.06316*.

The Most Expensive NFTs in History - Bankless Publishing. (2023). In *Bankless Publishing*. https://banklesspublishing.com/the-most-expensive-nfts-in-history

Treiblmaier, H. (2023). Beyond blockchain: How tokens trigger the internet of value and what marketing researchers need to know about them. *Journal of Marketing Communications*, *29*(3), 238–250.

Tumasjan, A., Sprenger, T., Sandner, P., & Welpe, I. (2010). Predicting elections with twitter: What 140 characters reveal about political sentiment. *Proceedings of the International AAAI Conference on Web and Social Media*, *4*(1), 178–185.

Wang, Q., Li, R., Wang, Q., & Chen, S. (2021). Non-fungible token (NFT): Overview, evaluation, opportunities and challenges. *ArXiv Preprint ArXiv:2105.07447*.

Wang, Y., Han, J. H., & Beynon-Davies, P. (2019). Understanding blockchain technology for future supply chains: a systematic literature review and research agenda. *Supply Chain Management: An International Journal*.

Wang, Y., Horky, F., Baals, L. J., Lucey, B. M., & Vigne, S. A. (2022). Bubbles all the way down? Detecting and date-stamping bubble behaviours in NFT and DeFi markets. *Journal of Chinese Economic and Business Studies*, *20*(4), 415–436.

Wang, Y., Wang, M., & Xu, W. (2018). A sentiment-enhanced hybrid recommender system for movie recommendation: a big data analytics framework. *Wireless Communications and Mobile Computing*, *2018*.

Weismayer, C. (2021). Investigating the affective part of subjective well-being (SWB) by means of sentiment analysis. *International Journal of Social Research Methodology*, *24*(6), 697–712.

Why NFTs are Dying? Is the Hype around NFTs Dead? (2023). In *CryptoTicker*. https://cryptoticker.io/en/nfts-dying-hype-dead

Wood, G. (2014). Ethereum: A secure decentralised generalised transaction ledger. *Ethereum Project Yellow Paper*, *151*(2014), 1–32.

Wu, C.-H., Liu, C.-Y., & Weng, T.-S. (2023). Critical Factors and Trends in NFT Technology Innovations. *Sustainability*, *15*(9), 7573.

Xavier, C. C., & Souza, M. (2020). *A Basic Approach for Extracting and Analyzing Data from Twitter BT - Special Topics in Multimedia, IoT and Web Technologies* (V. Roesler, E. Barrére, & R. Willrich (Eds.); pp. 185–211). Springer International Publishing. https://doi.org/10.1007/978-3-030-35102-1_7

Xhemali, D., Hinde, C. J., & Stone, R. (2009). *Naïve bayes vs. decision trees vs. neural networks in the classification of training web pages*.

Xu, Y., Cao, H., Du, W., & Wang, W. (2022). A survey of cross-lingual sentiment analysis: Methodologies, models and evaluations. *Data Science and Engineering*, *7*(3), 279–299.

Yue, K.-B. (2020). *Blockchain-augmented organizations*.

Zamani, M., Movahedi, M., & Raykova, M. (2018). Rapidchain: Scaling blockchain via full sharding. *Proceedings of the 2018 ACM SIGSAC Conference on Computer and Communications Security*, 931–948.

Zhang, X., Zhao, J., & LeCun, Y. (2015). Character-level convolutional networks for text classification. *Advances in Neural Information Processing Systems*, *28*.

Zhao, W. X., Jiang, J., Weng, J., He, J., Lim, E.-P., Yan, H., & Li, X. (2011). Comparing twitter and traditional media using topic models. *Advances in Information Retrieval: 33rd European Conference on IR Research, ECIR 2011, Dublin, Ireland, April 18-21, 2011. Proceedings 33*, 338–349.

Zheng, Z., Xie, S., Dai, H., Chen, X., & Wang, H. (2017). An overview of blockchain technology: Architecture, consensus, and future trends. *2017 IEEE International Congress on Big Data (BigData Congress)*, 557–564.