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Entwicklung einer Webanwendung zur Erkennung und Analyse von Wash-Trading bei NFT-Kollektionen auf der Solana-Blockchain

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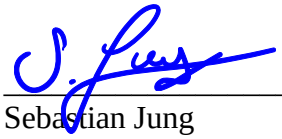
I confirm that this research in information systems is my own work and I have documented all sources and material used.



Gauting, 06.12.2022 Sebastian Jung

Abstract

With the rise of NFTs popularity, fraudulent activities to manipulate this market also increased. One of these techniques often used by scammers is wash trading, where the asset is traded between multiple accounts by one person or a group to increase the trading volume artificially. This fake demand can be very damaging to private investors, as they invest in an asset that does not have that value. Therefore, providing a website that allows users to check wash trading activity on NFT collections would be helpful. In this work, a methodology is developed to identify wash trades in the transaction history of an NFT collection on the Solana Blockchain. In addition, the user interface of a web page described above is explained, which we developed in the course of the work. Subsequently, this website is used to analyze the wash trading activities of small NFT collections.

Contents

Abbreviations

CPU	Central Processing Unit
DB	Database
DeFi	Decentralized Finance
ETH	Eth (Ethereum Native Token)
HMWT	Hello Moon Wash Trading Index[1]
ME	Magic Eden[2]
NFT	Non-Fungible Token
NFTM	NFT Marketplace
OS	OpenSea[3]
PoH	Proof of History
PoS	Proof of Stake
SCC	Strong Connected Component
SEC	Security and Exchange Commission
SOL	Solana Native Token
TPS	Transaction per second

[1] HelloMoon: *https://hellomoon.io/*
[2] Magic Eden: *https://magiceden.io/*
[3] OpenSea: *https://opensea.io/*

1 Introduction

1.1 A New Asset – NFT

Since 2017, in addition to well-known asset classes such as stocks, gold, and real estate, there has been a new form of investment, the Non-Fungible Token (NFT), proof of ownership and authenticity of a digital or physical asset stored on a blockchain [1]. Last year, this class reached a total sales volume of 25 billion U.S Dollars [2] which is a tenth of the GDP of the Czech Republic. Although the trading volume of 2022's first two quarters was already at the volume of 2021 ($25B), it showed a downtrend of 80% over the year, as indicated in *Figure 1.1*.

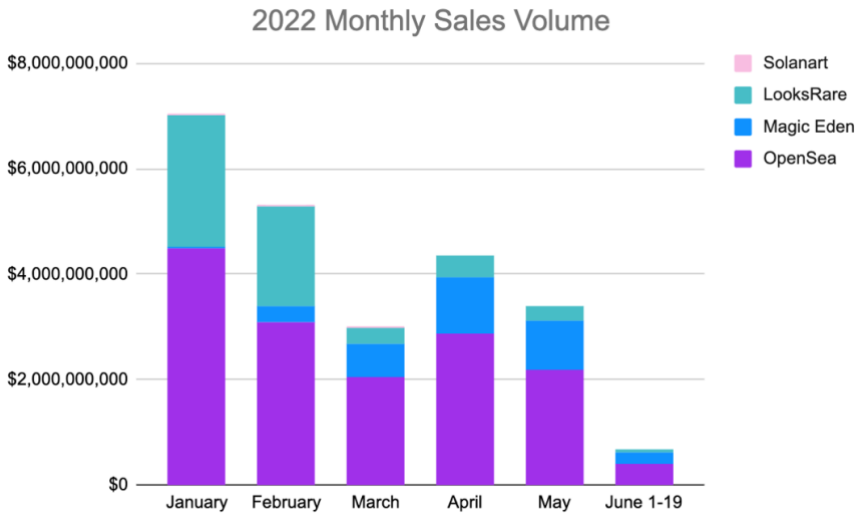


Figure 1.1: 2022 Monthly Sales of popular NFTMs[4]

This trend indicates a decreasing interest and hype [3] in NFTs and associated Web3 technology. Nonetheless, tokens of specific famous collections are still traded for enormous amounts. Most recently, CryptoPunk #2924 changed hands for 3,300 Ether (ETH) (equivalent at transfer: $4,45M) on September 28, 2022, on the Ethereum Blockchain [4].

Over the last two years, well-known companies like Nike, Adidas, and the game publisher Ubisoft have tried to make money with this new technology by selling NFTs

[4] Chart taken from "PROFIFOTO" (*https://www.profifoto.de/szene/notizen/2022/06/24/nft-umsatz-minus-80/)*

of their new shoes [5], collaborating with famous collections like the Bored Ape Yacht Club [6], or offering In-game skins as NFTs [7].

1.2 Security Issues of NFTs

Due to the lack of legal regulations in the market where NFT trades take place, there are some issues with NFTs regarding security and stability that are used as arguments against their use, especially by critics. This lack of regulations is because of the broad spectrum of types of NFTs. Namely, a few NFTs are regulated by already existing securities legislation in, for example, America, but only if the buyer can justifiably expect a profit [8]. One resulting big problem is the simple implementation of money laundering and wash trading. A deeper explanation of the accessible wash trading practices will be mentioned in *Section 3.1* and *Section 3.2*.

Another issue is the uncertainty that a collection is not a scam. Namely, it is common for new collections to share a road map in which the collection creator shares plans, like introducing token utilities. The continuous adherence to these aims, as well as their size (e.g., live events exclusively for NFT holders), can determine the overall value of a collection because they motivate people to buy their NFTs and create a popular community. But if these are not complied with, these collections are considered scams and flagged by most marketplaces, which leads to a massive dump in the price of a single NFT out of the collection. Such a loss of value can be compared with a company's bankruptcy in which one has invested its money via the stock exchange.

Such a flunk in popularity has happened to the Solana collection “Nasty Nerds”. The creators promised that after six months of publication, NFT holders could apply for a “Circle Of Brilliance”, which would have worked like the board of a company [9]. However, this procedure never took place, which is reflected in a price collapse of the tokens and a flag on Magic Eden (ME), a popular NFT marketplace on Solana, that the project is a scam [10].

1.3 Motivation

Trading of NFT collections can take place on many different blockchains, which will be explained in *Section 2* in more detail. However, this work focuses exclusively on the Solana Blockchain since similar analyses have already been made on Ethereum, the largest smart-contractable blockchain.

Furthermore, Solana is considered the new up-and-coming, high-speed blockchain [11], being the head-to-head opponent to Ethereum. This raises interest in how such wash trading activities occur in Solana's NFT ecosystem. Therefore, a user-friendly website would allow anyone to check the wash-traded volumes of NFT collections and their share of the total volume. This would protect private investors from dangers that can cause a total loss of invested capital.

1.4 Structure of the Essay

The paper aims to develop a methodology to detect wash trading in Solana NFT collections and implement a web app to inform users about these activities. In the beginning, the paper points out the general problems and dangers of wash trading. Then, the background information needed to understand the blockchain technology of Solana and its NFT technology will be presented. The central part of this work forms the development of the tool together with an analysis of wash trading activities of selected NFT collections on the Solana network. The paper also introduces the user interface of the built website and explains how the algorithm used in this work detects wash trades. This web application will then be used to analyze the wash trading activities of small-sized NFT collections to identify any relations and patterns among specific attributes of a collection. To check if the explained methodology correctly identifies these wash trades, we compare the results with the one from the NFT analysis website called Hello Moon[5], which provides a Wash Trading Index for each collection. In the end, a conclusion about both the usability of the website and the findings in the wash trading activities will be made, followed by mentioning future work, which would help to improve user experience, efficiency, and the broad usability of the website.

[5] Hello Moon: *https://www.hellomoon.io/nfts/top-projects*

2 Theoretical Basics

The following section explains essential technical terms and topics related to NFTs in general and on the Solana Network, which are the base for the following investigation.

2.1 Solana Blockchain

Solana is an open source blockchain project aiming to provide a scalable, fast, cheap, and decentralized blockchain solution [12]. As a layer one blockchain like Bitcoin, Solana offers the basic infrastructure, such as processing transactions [13]. Its whitepaper[6] was released in 2017 by Anatoly Yakovenko, and the network launched three years later, in March 2020. Solana is based on a Proof of Stake (PoS) consensus mechanism together with Proof of History (PoH).

Solana's PoS works as Nodes with staked SOL vote for a leader who processes transactions by ordering them and writes the network state. Verifiers, the nodes with staked SOL, read this state, verify it, and vote to confirm it (see *Figure 2.1*).

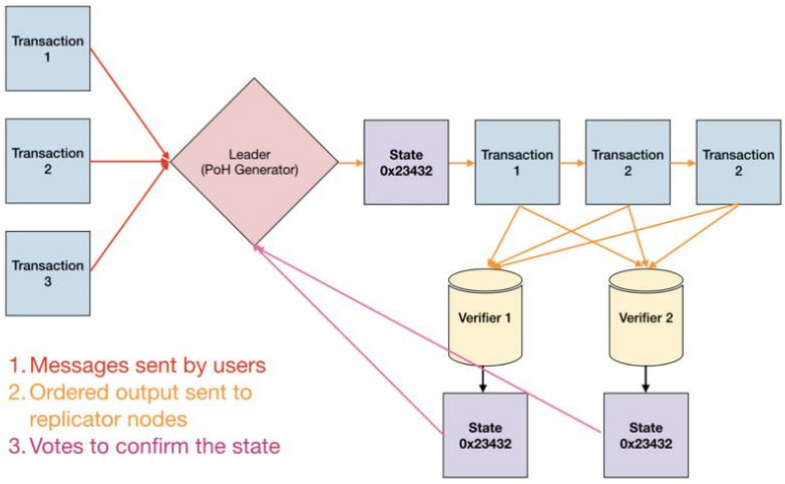


Figure 2.1: Transaction flow of Solana[6]

[6] Solana Whitepaper: *https://solana.com/solana-whitepaper.pdf/*

To ensure the correct order of the transactions, the leader is computing a sequence of hashes, in which the output is the input of the following function call. Everytime an event comes to the leader, it is put into the input of the next called hash function. This PoH system is based on the nature of the preimage- and collision-resistant sha256 function. These two properties provide that first, the input of the function cannot be determined by the output, and second, it is difficult to find two inputs that give the same output. That's why the sequence can only be computed on one single core of the CPU and thus not be parallelized, through which the generated sequence can be used as proof of passed time. The network has agreed on a universal time represented by this sequence, so there is no need for communication between single nodes regarding the chronological order of transactions because the order can the determined by the generated hash sequence. Verifiers must verify that the sequence is valid and that the time really passed. This verifying process can be parallelized, leading to the high throughput of transactions [14]. This protocol makes it possible for the network to speed up to 700,000 transactions per second (TPS) and, under perfect conditions, reach up to 24 million TPS [11].

On Solana's main network, the transaction speed is currently at ~2,000 TPS [15], but still 200 times faster than Ethereum with ~14 TPS [16] and 285 times faster than Bitcoin with ~4 TPS [17]. The better scalability even leads to a low transaction fee of an average of $0.00025 [18]. In comparison, the average cost, also called gas price, of a complex Ethereum transaction like minting an NFT or swapping Tokens on Uniswap can be up to $400, depending on the workload of the network [19]. Overall, Solana is considered the cheaper and faster alternative to Ethereum, especially regarding NFT and Decentralized Finance (DeFi).

2.2 Smart Contract

Smart contracts, also called programs on Solana, offer a convenient way to automatically manage legally relevant data stored on a blockchain and execute an agreement between multiple instances. These two parties can be right away sure about the outcome of the agreement since there is no need for trust in a centralized institution because the smart contract is decentralized hosted on the network as well as open source.

Smart contracts are used on famous blockchains like Ethereum, Solana, Cardano, and even Bitcoin. The most popular use happens on Ethereum because of the prominent market cap of its native token on the one hand and its early and first implementation of this technology on the other hand. Today there are more than 2.5 million of these deployed on Ethereum [20].

However, Solana approaches this technology differently than Ethereum or any other high-performant blockchain, contributing to the high transaction speed of Solana. Namely, data, which will be modified by the smart contract, is not stored inside the transaction or the instruction but is defined before the transaction is executed. Thus, these transactions are stateless, enabling Solana to manage multiple instructions simultaneously and in parallel because the transactions that modify the network state at two different places can be executed at once [21]. All in all, smart contracts make the system of NFTs possible in the first place, which will be explained deeper in *Section 2.3* and *Section 2.4*.

2.3 NFTs on Solana

In the Solana network, Metaplex provides a standard that most NFTs use. Metaplex is a broad offer of different programs that focus on an easier implementation of NFTs on Solana. Because of its high popularity, this subsection will explain the system called “Token Metadata”, which is one of the mentioned programs [22].

The actual data of an NFT, i.e., the image URL, the metadata, the collection, etc., are stored in an account called “Metadata Account” which is a program derived address (PDA) from the Mint Account. A PDA is similar to a public key but does not have any corresponding private key because it is derived from a programmatic account. Therefore, it can only be signed by this specific account [23]. The Mint Account regulates the supply of a token, which is one for NFTs. This property exists since traditional tokens, such as stablecoins, use the “Token Metadata” program, too. Also defined by the Mint Account are the decimals, which represent how fine a token can be split, i.e., describes the decimal places. In the case of NFTs, this value is zero. The mint authority, also stored by the Mint Account, defines an address that could mint new

tokens. This value is set to none to make sure the NFT is unique and cannot be created multiple times.

There is no direct reference between the wallet holding the NFT and the Mint Account. This dependency is stored in the Token Account, which thus keeps the number of tokens held by the wallet [24].

The following *Figure 2.2* illustrates the program "Token Metadata" explained above.

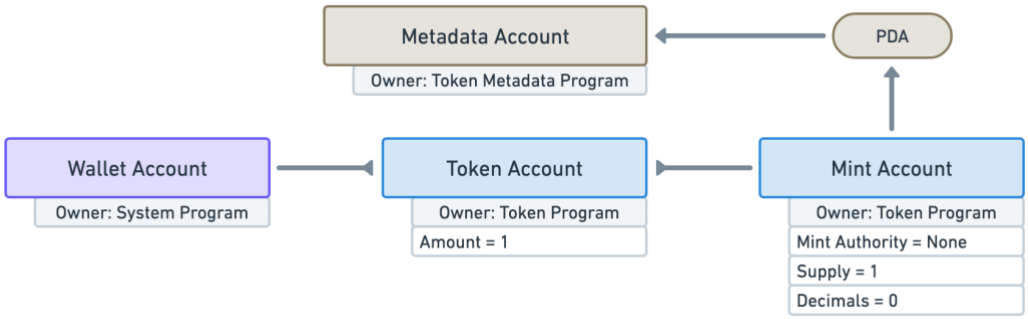


Figure 2.2: Metaplex' Token Metadata[7]

2.4 Buy – Sell NFT Process

To make the NFTs useful, offering contracts to trade them is essential. The trade of an NFT can happen in different ways. The typical way to trade or sell such a unique token would be by using an Escrow smart contract. Marketplaces can easily implement such an escrow because of the low transaction fees on Solana. On Ethereum, this practice would be much too expensive because of the possible high gas fees, which is why the largest NFT marketplace on Ethereum OpenSea (OS) does not use an Escrow for offering sales [25].

An Escrow is a traditional, easily implemented smart contract and serves as the "Hello World" program when starting to write smart contracts. It's a legal agreement between two instances that a third party (in this case the program) temporally gains access to assets that shall be traded (see *Figure 2.3* steps 1 and 2). The third party then gives these assets to the buyer/seller as soon as both instances provide their aggreged asset [26] (see *Figure 2.3* step 3).

[7] Image from Metaplex Docs (*https://docs.metaplex.com/programs/token-metadata/overview/*)

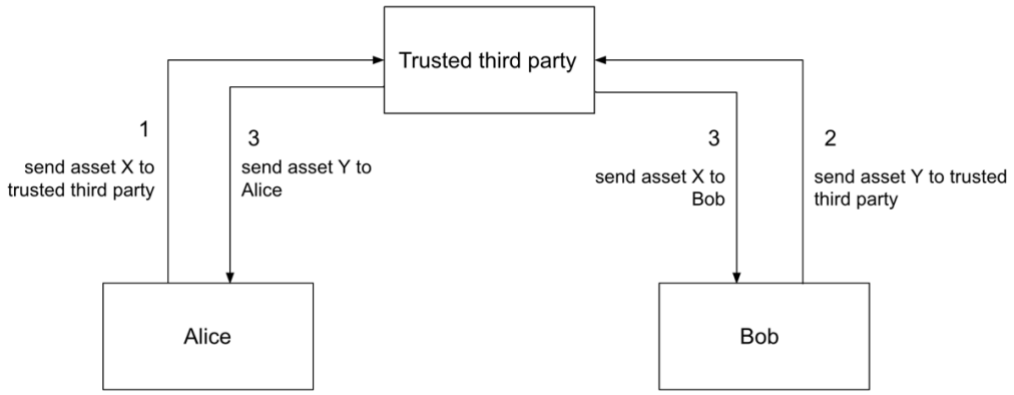


Figure 2.3: Illustration of simple escrow[8]

A more modern way to execute a trade of assets is the "Auction House" program by Metaplex. Its escrow-less nature provides a leaving of the asset from the wallet only as soon as the trade is executed [27]. Large Solana marketplaces like ME have announced to implement Metaplex ecosystem, including Auction House [28]. It is not necessary to explain this program for this research because of the complexity and the little impact on our study.

[8] paulx: *https://paulx.dev/blog/2021/01/14/programming-on-solana-an-introduction/#what-is-an-escrow*

3 Wash Trading – a Big Problem

Wash trading defines the malicious practice in which one or multiple allied entities assume the role of seller and buyer in a financial instrument trade and repeat the same trade numerous times. This form of market manipulation was prevalent in the 1930s, but since the Commodity Exchange Act of 1936, this action has been illegal in regulated markets in the United States of America [29], which is why it is hardly used in traditional markets anymore. Nevertheless, these days this malpractice is widely spread in the crypto market. According to a report submitted to the Securities and Exchange Commission (SEC) in 2019 by the Crypto exchange BitWise, it is an essential issue in the crypto market. According to their research, 95% of the recorded volume of crypto exchanges was feigned using wash trades [30].

3.1 Dangers of Wash Trading

Scammers mainly use wash trading to artificially increase the trading volume of a specific asset, which conveys the impression that the security has a higher demand than it actually has [31]. This fake information harms private investors by motivating them to make risky bad investments which, in the worst case, can lead to loss of all invested capital [32] [33]. Following this kind of danger, scholars have warned that many big crypto exchanges like HitBTC, Bibox, and CoinMex are using wash trades to pretend to have liquidity and be popular among crypto investors by increasing their sales volume by 70% [34]. Because investors have to trust this information, this trust can easily be abused to create financial damage. For example, the lack of liquidity needed to execute fast trades in precarious market situations [35] can hurt the financial situations of investors.

3.2 Wash Trading on NFT Marketplaces

Due to the nature of the technology of blockchains like Solana and Ethereum, traders do not have to identify themselves when they want to trade with NFTs on large marketplaces like ME or OS [36]. One user can easily have multiple instances of unique addresses on the blockchain, which are treated as two unique individuals. This makes wash trading and money laundering with NFTs more attractive than traditional assets, whose impact can be seen on small marketplaces.

In August 2022, the one-week trading volume of the NFT marketplace X2Y2 increased by 470% and was thus the largest marketplace in terms of trading volume for one week [37], although it only has roughly a tenth of the users of the largest marketplace OS [38].

However, investigations have shown that the high volume was not caused by the large crowd making many wash trades but by individuals doing wash trading with high prices, as the number of transactions tends to decrease. During April, the number of wash trades climbed to 7,000 transactions; until July, it declined to 20 (see *Figure 3.1*). In contrast, the volume of these wash trades increased [39] (see *Figure 3.2*). From this, it can be concluded that there is consolidation among the few wash traders, who trade up to 5,000 ETH per day.

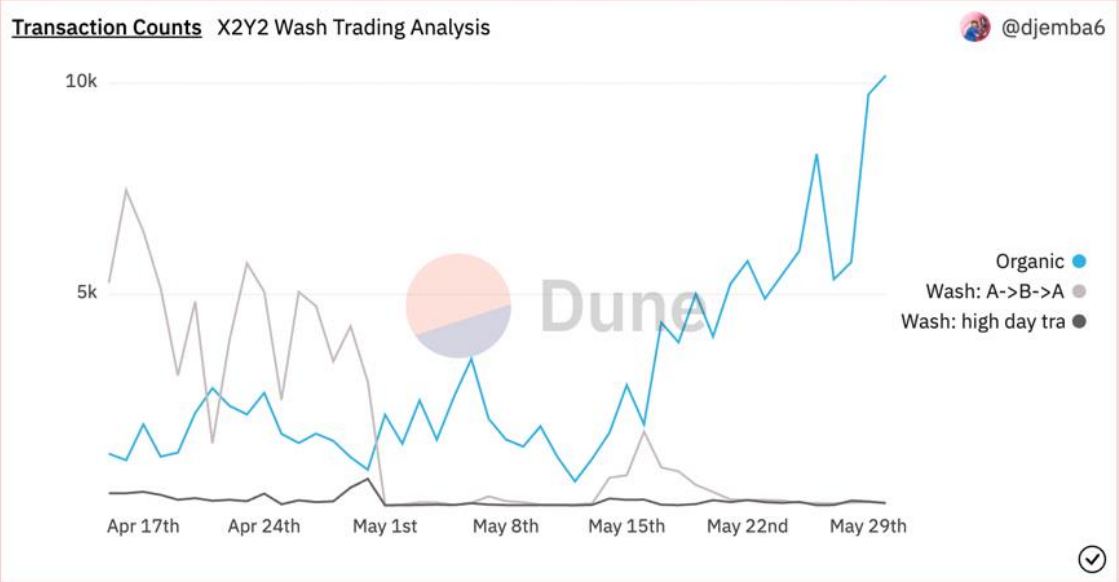


Figure 3.1: Transaction Count on X2Y2 sorted by type[9]

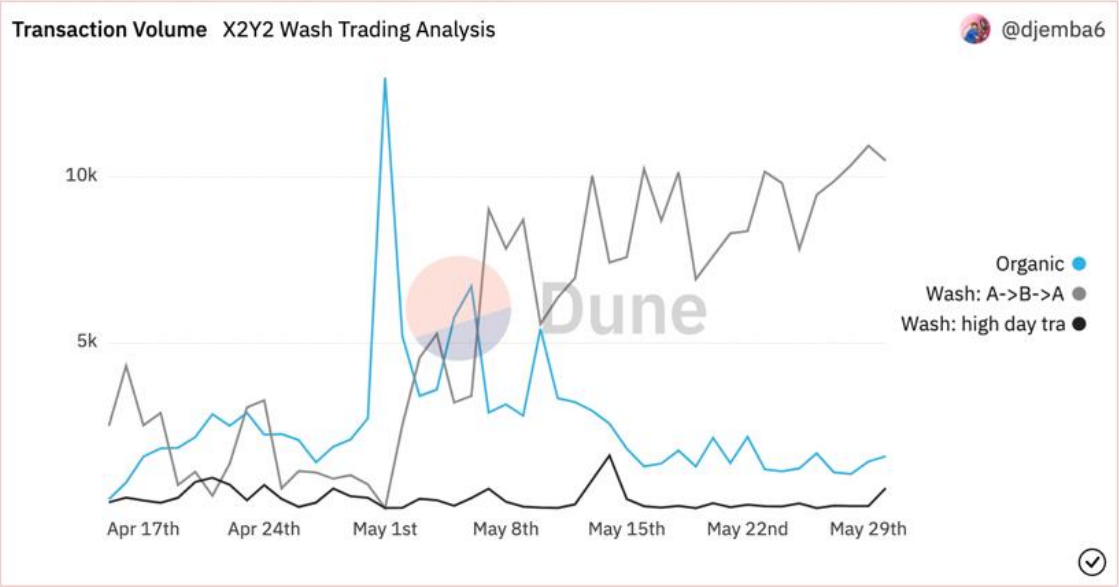


Figure 3.2: Transaction Volume on X2Y2 sorted by type[9]

[9] Dune: *https://dune.com/djemba6/x2y2-trades*

3.3 Detecting Wash Trades

Detecting such wash trades can be approached with a few different techniques. In this subsection, the focus will be on detecting wash trades among NFTs trades due to the specialization of the paper on this topic.

A prominent and intuitive approach is investigating the transaction history of suspicious addresses. If funds were sent to an account right before NFTs were bought with this account for a similar amount, this trade could be considered a wash trade. And if the sender of the funds is the seller of the NFT and the receiver of the funds is the buyer of the NFT, the probability of a wash trade increases. This technique is, for example, used by the website "Hello Moon" to calculate a wash trading index for a collection [40].

The technique we chose for our algorithm is more concentrated on the transaction history of a collection represented in a graph, which is searched for the occurrence of strongly connected components (SCC). The concept of SCCs will be explained later in *Section 4.1.3*. If such an SCC occurs more than five times, all trades in this cycle and remaining among nodes from the same SCC are considered wash trades. We decided to use this method since the first approach mentioned is already practiced by the website Hello Moon to calculate their index.

4 Methodology

To execute the research, we built a user-friendly website[10] hosted on Hetzner Cloud and available for everyone. The website's code is open source and can be found on GitHub[11]. The following subsections explain how the website is built, how the data flow happens, and how we implemented the algorithm mentioned in *Section 3.3*. In *Section 4.2*, overall difficulties while implementing and which are still present will be discussed.

4.1 Webapp for Examination

4.1.1 Website

For implementing the website, we chose the full-stack JavaScript framework Next.js, because of its easy and convenient implementation of frontend and backend and the fast and efficient communication between them in production. The following text will explain the website's user interface by referring to the numbers displayed in multiple figures.

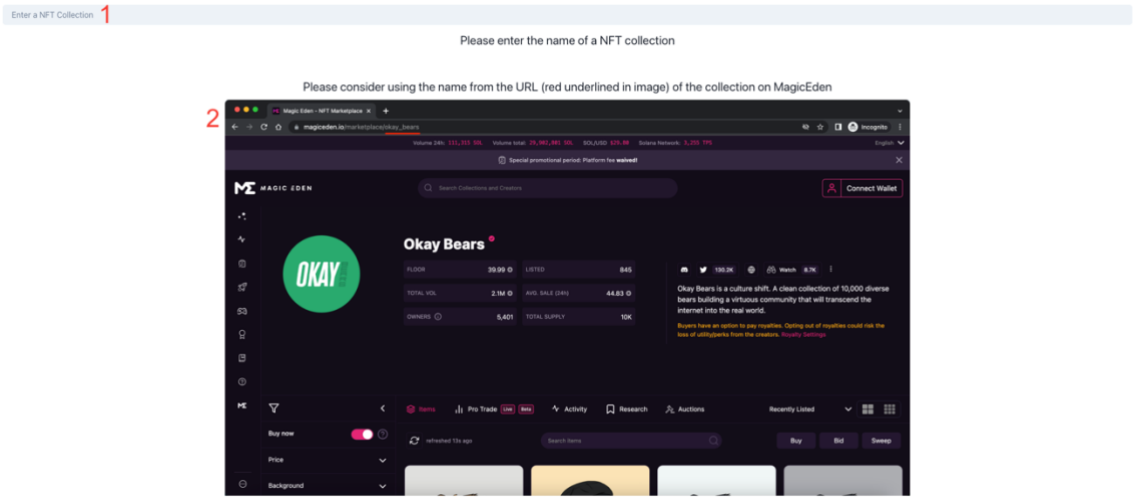


Figure 4.1: Website landing page

[10] Deployed application: *https://xyz.pizza/*
[11] GitHub repository: *https://github.com/basti394/nft-research/*

The website's landing page, as shown in *Figure 4.1*, consists of two main components. The first one is the search bar referred to with the number 1. To search a Solana NFT collection, the name of the collection must be written in this text field, and the button Enter must be pressed. Important to say is that the word that must be put into the search bar has to be the red underlined part (last word) from the URL of the ME site of the collection, which is shown in the central image on the landing page (see reference 2). To get this URL, you first have to search the collection on ME.

After searching for a collection, a loading screen will appear, which can remain for a maximum of roughly ten minutes, depending on different factors, which will be discussed in both *Section 4.1.2* and *Section 4.2*.

As soon as the loading screen disappears, the window shows the transaction history of the collection with some additional pieces of information, as illustrated in *Figure 4.2*.

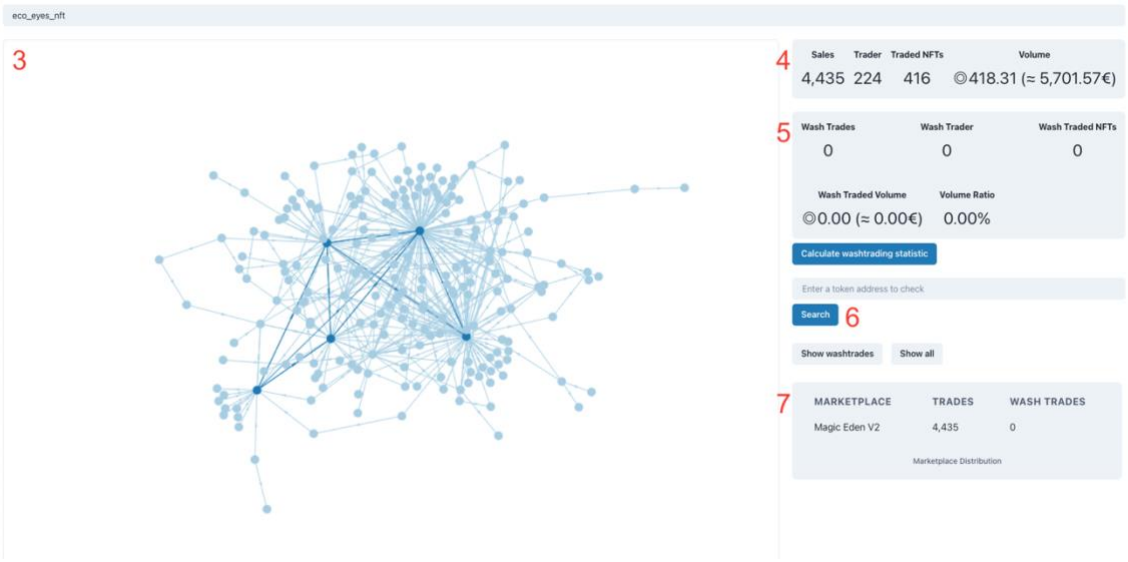


Figure 4.2: Screen with transactions of searched collection

The main part of this screen consists of the canvas for the graph (3), which displays the transactions made with the NFTs from the collection. The containing nodes represent trades or accounts on the Solana Blockchain, and the edges are the sales between them. As the graph in the figure above shows, some nodes have a darker blue color than the rest, along with the edges connecting them. This indicates traders and transactions flagged as wash traders or wash trades by our algorithm. The remaining graph is colored

more brightly to highlight the contrast between wash traders or wash trades and those who are not. Multiple trades between nodes are displayed as one edge to avoid complex rendering calculations at too many transactions among traders and to improve the graphs' readability. But to get information about the transactions between two addresses, the specific edges need to get hovered to let a small box appear containing the required information, as shown in *Figure 4.3*. In the top left corner, the number of transactions is shown, followed by information about each trade, containing the price, the marketplace, and the address of the token's mint account (see *Section 2.3*).

Figure 4.3: Tooltip showing information about trades

The right side of the screen shown in *Figure 4.2* is filled with the mentioned additional information. The component labeled with the number 4 presents the total number of visualized trades and the number of traders who have executed those trades. The next two values indicate the number of traded tokens and the total trading volume created with these trades, displayed both in SOL and in the current amount of Euros. These figures differ from those on the respective page of ME, which is further discussed in *Section 4.2*. Below that, the following component labeled with the number 5 displays information about the calculated wash trades of the specific collection. It comprises the number of wash trades detected by our algorithm, total wash trades, and wash traded NFTs. On the bottom part of component 5, the wash traded volume created by the wash trades is displayed along with the ratio to the total trading volume.

At first, Component 5 won't show any data. To get an insight into the wash trading statistics, the blue colored button labeled "Calculate wash trading statistics" below Component 5 must be pressed to get the actual values displayed. Together with components 4 and 5, box 7, containing a table, in *Figure 4.4* on the bottom of the page will also change its column "Wash Trades" to the actual number of wash trades on each marketplace.

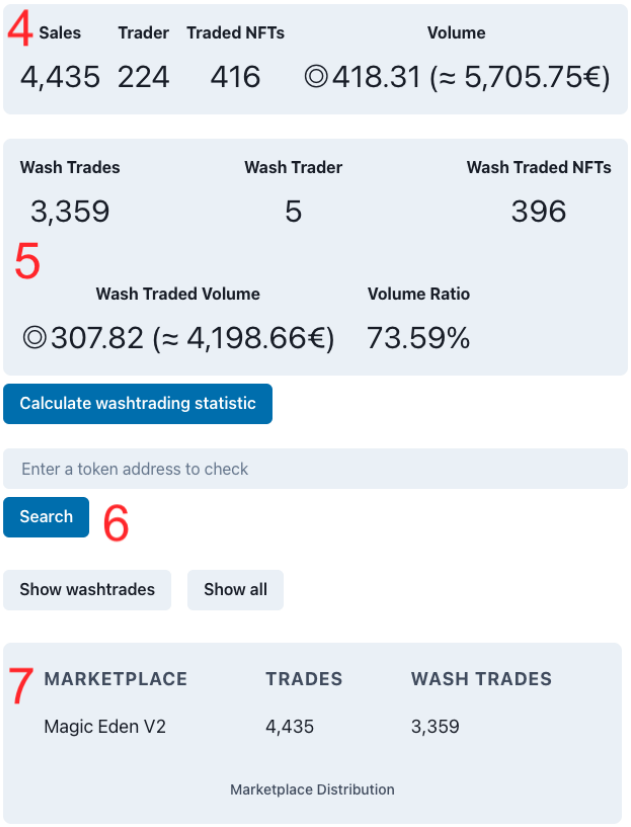


Figure 4.4: Calculated Wash Trading Statistics

The second search bar labeled with 6 in *Figure 4.4* is used to search for a specific token. The graph on the left (see *Figure 4.5* Reference 3) will then only show the trades or wash trades of this one NFT. In addition, the rest data in the components (4, 5, 7) on the right side will also change their values to match those with the displayed trades. To search for an NFT, the address of its mint account (cf. *Section 2.3*), the same as displayed at the bottom of the tooltip of the edges (see *Figure 4.3*), must be typed into the text field and the blue colored button that says "Search" must be pressed. The following *Figure 4.5* gives an example of the screen when searching for an NFT.

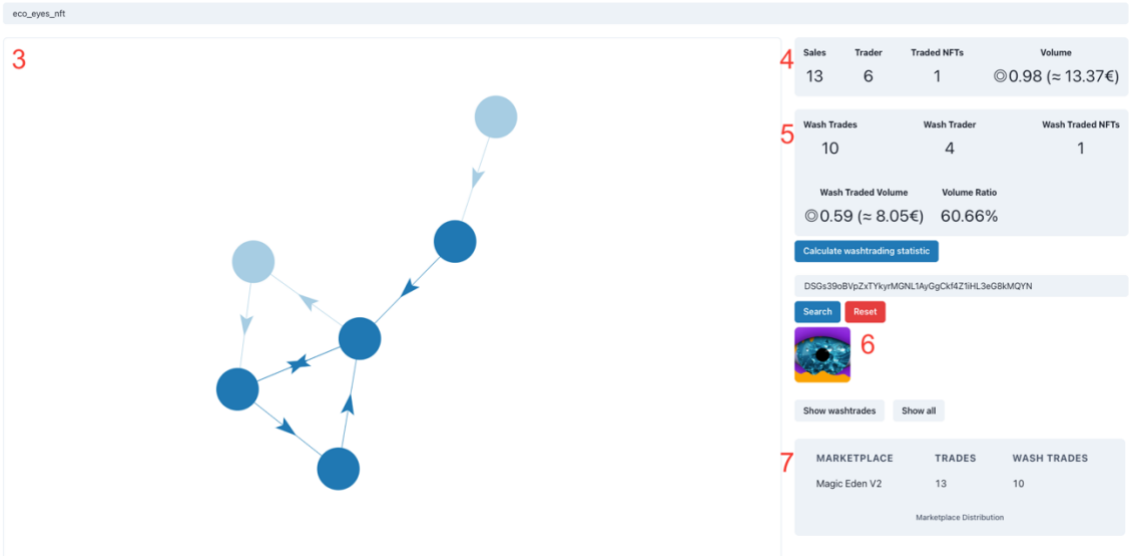


Figure 4.5: Screen with transactions of searched NFT

The table already mentioned above labeled with 7 in *Figure 4.5* and *Figure 4.2*, offers an insight about trade distribution among NFT marketplaces, like ME or SolSea. It contains three columns, the first showing the name of the marketplace, the second showing the amount of all trades done on this platform including wash trades. The third row will represent only wash trades that happened on the respective marketplace.

4.1.2 Data Flow

The transaction history of each collection ever searched on the website is stored in a Neo4j[12] database (DB), a native graph database, hosted on Hetzner Cloud. This DB perfectly fits the needs of the web app as it stores the data as relationships between the nodes, instead of in tables like common relational DBs like MySQL.

When a collection is searched, an API request is sent to the backend. Firstly, it will be checked if the collection is already stored in the DB. If so, this data is returned, but if not, the entire event history of the collection is requested from the public API of the marketplace ME[13] from the endpoint GET /collections/:symbol/activities. The path variable "symbol" is the name put into the search bar in *Figure 4.1*.


```
{
    "signature": "4fc815B782tJVkhZJtDqESyMNUtLX86pzKbRQBqdZEXtnV18FHFWh3cazupwtpKtbZASH9WRTHNRsUSbu7vvT5sj",
    "type": "buyNow",
    "source": "magiceden_v2",
    "tokenMint": "84YRuHAPjb59ZfsCw41eCtLwRhJThow868AgocPp7ntj",
    "collection": "degods",
    "collectionSymbol": "degods",
    "slot": 161938534,
    "blockTime": 1668863711,
    "buyer": "CKJ8UmRC55T6Px8R9H7kfQLSBfv3Wk56ygpDFN2KNh9q",
    "buyerReferral": "",
    "seller": "2UHdhZCt8EtD5zfsDb474aiZZSyV4aBKd1jCFijxf6BV",
    "sellerReferral": "",
    "price": 277,
    "image": "https://metadata.degods.com/g/4917-dead.png"
},
```


Figure 4.6: Returned JSON from ME API

This endpoint returns a list of JSON objects shown in *Figure 4.6*. The list also includes other activities like bids and listings, which are defined by the property "type", but since these events are not necessary for calculating wash trades, they are removed from the list. Because the API has a rate limit of two queries per second, the request will take some time if the collection is searched for the first time.

After storing the filtered data in the DB, the server formats the data received from ME. For us, only the properties "source", "collection", "tokenMint", "buyer", "seller", "price", and "image" are important. Therefore, this data is the only one stored in our DB.

[12] Neo4j DB: *https://neo4j.com/*
[13] ME API: *https://api.magiceden.dev/*

To calculate the wash trading activities of the given transaction history well and without spending much time on a complex deep-first search implementation, a graph class from geeksforgeeks.org[14] based on Tarjan's algorithm is used to calculate the SCCs.

The results of that algorithm are passed on to a self-implemented function to calculate if an SCC can be considered a wash trade. This algorithm will be deeply explained in *Section 4.1.3*. The returned data is then used to flag the nodes and edges that were stored in the database previously.

After this procedure, the requested collection will be queried from the DB using the native Neo4j driver for JavaScript and the query language Cypher. In the beginning, we implemented a GraphQL API, which then was too time intensive to query, resulting in the approach to query the database directly. After the data is returned it is formatted to the format used by the frontend library, which renders the graph. This format will be further explained in the following *Subsection 4.1.3*. For searching specific tokens and receiving the wash trading information about transactions, our API has additional endpoints providing the necessary data.

[14] GeeksForGeeks Tarjans's Algorithm: *https://www.geeksforgeeks.org/tarjan-algorithm-find-strongly-connected-components/*

4.1.3 Algorithm

The algorithm for detecting wash trades relies on Tarjan's algorithm mentioned in *Section 4.1.2*. A deeper explanation of how Tarjan's Algorithm works can be found in the 19th lecture "Depth First Search and Strong Components" of the Carnegie Mellon Universities' School of Computer Science [41]. This Algorithm is used to find SCCs from a dataset representing a directed graph.

A graph or an inside component can be declared as strongly connected if one node can be reached from every other node in the graph or the component. A corollary to this is that some cycles in a directed graph are also strongly connected components, like {a, b, e} and {f, g} in *Figure 4.7*. But the two cycles {c, d} and {h, d} cannot be separately declared as strongly connected, which leads to the definition that an SCC is the largest directed cycle. Therefore, the component {c, d, h} is strongly connected.

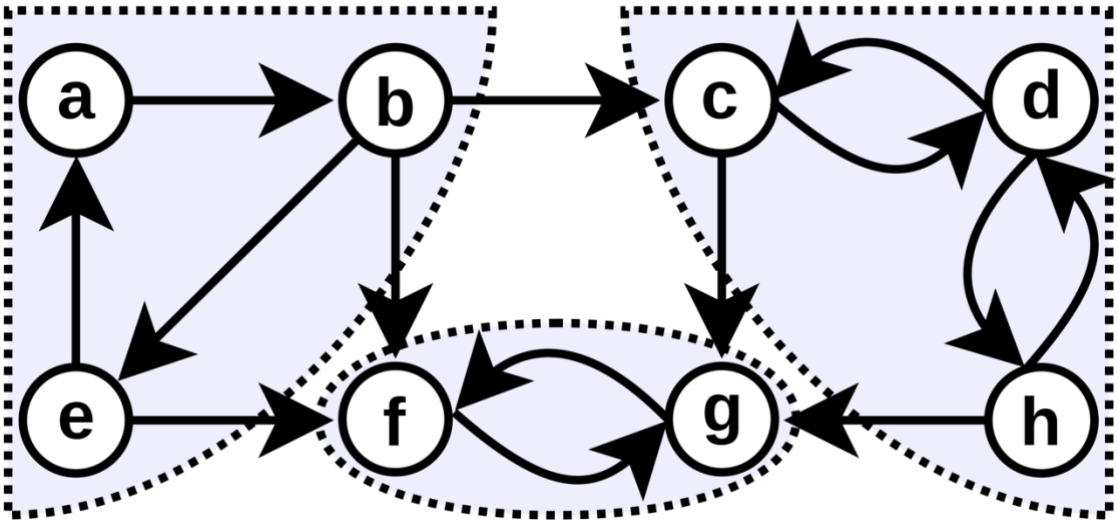


Figure 4.7: Graph containing three SCCs[15]

However, an SCC does not necessarily have to contain any directed cycle because a cycle cannot contain any repetition of nodes and edges. Consider having a graph as illustrated by *Figure 4.8*. This entire graph is strongly connected but does not contain any directed cycle which covers every node, because to ensure that the starting node is the same as the ending vertex, the edge {f → a} would have to be visited twice.

[15] Wikipedia: *https://en.wikipedia.org/wiki/Strongly_connected_component#/media/File:Scc-1.svg*

Therefore, if we just looked at cycles, either the links [{a → b}, {b → f}] or [{a → e}, {e → f}] would be missed and not identified as wash trades.

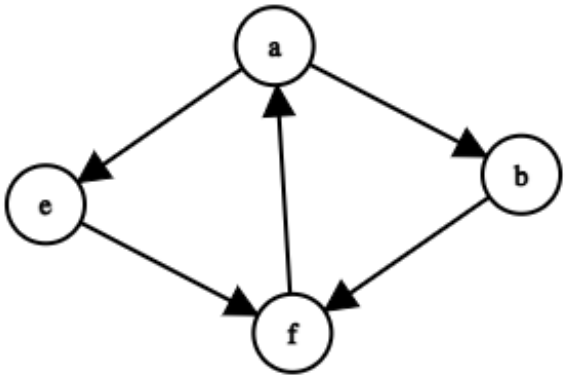


Figure 4.8: SCC without any cycle

After running Tarjan's Algorithm to detect such SCCs, our algorithm explained in *Section 3.3* then detects if the transactions in the found SCCs are considered as wash trades or not, by counting their occurrence, by running Tarjan's algorithm multiple times, always with a slightly edited graph. After each iteration, the found SCCs are removed from the graph and stored in an extra array called "finalSCCs". With this method, the algorithm has an array with all SCCs, even the ones that are duplicates, from which it can check the number of occurrences.

The instruction data of our algorithm consists of two arrays, "allNodes" and "allLinks", one containing all nodes of the graph, the other one storing the links between those nodes. This approach is because the used UI library that renders the graph also takes these two arrays as input. Since the Graph class from GeeksForGeeks uses Integers for labeling the nodes, the nodes in the array containing the links must be parsed so that the current label, which shows the account address, becomes an integer. For that, the algorithm converts this String to the number of the node's index in "allNodes".

The following *Figure 4.9* shows the algorithm written in pseudo-code to give a better understanding of how it operates.

```
Algorithm 1: Detect wash trading
  Result: Array with nodes under which wash trading has taken place
  allNodes = array with all nodes;
  allLinks = array with all links between nodes;
  for link in allLinks do
  |  replace label of target and source nodes with its index in allNodes array;
  end
  graph = new Graph();
  for parsedLink in allLinks do
  |  add parsedLink to graph;
  end
  finalSCCs = [];
  SCCs = graph.SCC;
  sccsFound = if SCCs.length > 0 then
  |  true
  else
  |  false
  end
  while sccsFound is true do
  |  for SCC in SCCs do
  |  |  remove SCC from graph;
  |  end
  |  add SCCs to finalSCCs;
  |  SCCs = graph.SCC;
  |  sccsFound = if SCCs.length > 0 then
  |  |  true
  |  else
  |  |  false
  |  end
  end
  wtSCCs = [];
  for SCC in finalSCC do
  |  if SCC appears more than 5 times in finalSCC then
  |  |  add SCC to wtSCCs
  |  else
  end
  return wtSCCs;
```

Figure 4.9: Algorithm to detect wash trades

This algorithm will only be executed if a collection is searched and stored in the database for the first time. This leads to a better user experience, as the server does not have to loop through all transactions every time, which also does not overload the server and decreases the time a user must wait for a response in the front end.

This single-calculation approach works because the data is not updated anymore once it is saved in the database. We chose this static data handling because of the low requests per seconds rate the API offers as mentioned in *Section 4.1.2* and *Section 4.2*.

4.2 Overall Limitations

With the development of the website, some difficulties appeared, causing problems that restrict the user experience and efficiency of the website. One limitation we discussed, to some extent, is the long loading time when a collection is searched for the first time. As mentioned in *Section 4.1.2* that problem occurs mainly because of a strict rate limitation of the ME API and because of the lack of natively filtering API results as mentioned. The execution of Tarjan's algorithm and our own algorithm to calculate the SCCs and wash trades also increases the loading time since it contains multiple loops over every found SCC as illustrated in *Figure 4.9*. The specific use of the algorithms mentioned at the end of *Section 4.1.2* results in data that is not up to date after a certain amount of time. That limits the accessibility of newer transactions to the user since it is never updated anymore.

The limited data access is also amplified by a current bug in the ME API, causing a limit of 15,000 activites that can only be requested. The bug is a wrong interpretation of the given offset number. Namely, every number higher than 15,000 is interpreted as a negative number, and therefore the API throws an error.

A problem, which limits the readability of the shown graph on the website, is clutter when showing a high number of transactions. This is increasingly the case, when the shown transaction in the graph is changed and then switched again to the original ones. The previous order of nodes and edges will also be drastically changed when doing this. Because we couldn't identify any error in our own source code, we submitted an issue to the library's repository on GitHub[16].

[16] GitHub Issue: *https://github.com/vasturiano/react-force-graph/issues/389/*

5 Results

At the beginning of this research, we wanted to group 60 collections by their total volume, for a clearer and more informative examination of the NFT-Collections. But because of the known issues with the ME API mentioned earlier, the requests for large and medium collections only return a fraction of the actual transaction history. For realistic research, this is not suitable, which is why we decided to look at small collections with a small number of activities to receive a realistic portion of the entire transaction history. All the following data taken for this research from our website only contain transactions until the 18th of November 2022. The collections that we have chosen to analyze must meet several criteria. These have different reasons, which are explained below.

5.1 Selection Criteria

First, the collections must have a certain share of wash traded volume so that these trades can be analyzed and categorized. The Wash Trading Index of the NFT analysis website Hello Moon rates collections according to their wash trading occurrence. Collections that will be analyzed in the following have mainly a rating of > 90 because they have the most wash trading. However, to get a more diversified picture, collections with a rating of < 90 were also selected. To benchmark the algorithm at the beginning of the results, four collections with no wash trades were also selected.

Another criterion is the size measured by the total trading volume of the collection. Due to the mentioned circumstances with the ME API, these collections must not be too large. Otherwise, the covered part by our DB of the total volume is too marginal, and therefore no representative investigations can be carried out. All selected collections have a total trading volume of below 2,000.00 SOL and a minimum volume coverage of 30% by our fetched data. The highest coverage we have is 100%, and the lowest is 30%. To request the data, the collections must be listed on Magic Eden.

5.2 Benchmark with Hello Moon's Wash Trading Index

For the following analysis, we used the data generated by our web app. To validate our results, we benchmark our algorithm and compare the results with another third party.

For that, we use the Wash Trading index from Hello Moon (HMWT Index) mentioned in *Section 5.1*, by analyzing 18 collections that meet the mentioned requirements on our website and comparing the values with the values of the index. These 18 collections will be used in the further course of the research.

Table 5.1: Wash Traded Share compared to HMWT Index

	NFT Collection	Wash Traded Share	HMWT Index
1	Anime Cute Girl	95.46%	100
2	Bear Cleo Club	95.12%	99
3	Alien Worlds	91.27%	95
4	Bulldog Mafia	88.58%	99
5	SolTV	85.51%	81
6	Samuway	84.38%	99
7	Last Retronauts	82.82%	99
8	Wack Wack	78.73%	99
9	Eco Eyes	73.59%	100
10	Gothic Demon	70.40%	95
11	Degen Reptilian	59.66%	99
12	ABC Pirates	12.22%	80
13	Trippin' Baby Ape Tribe	9.39%	51
14	BunnyToons	1.70%	35
15	Goblin Army	0.00%	72
16	Halo Gods	0.00%	0
17	Gyris: The Mara	0.00%	0
18	DooDoo	0.00%	3

Table 5.1 depicts the HMWT Index value for all 18 chosen collections, sorted by the share of wash traded volume, found out by our algorithm. What can be seen well from this plot is the agreement with the upper and lower data sets. Collections with a high HMWT index value are recognized by our system to 87.5%. Collections that do not show any wash traded volume according to Hello Moon are correctly recognized by our system to 100%. This error rate in the first cases is due to the not 100% volume coverage in our database, because of the known bug at ME.

The algorithm can be considered accurate as it correctly categorizes collections and estimates activity consistent with Hello Moon's index, and therefore suitable for the following analysis.

5.3 Wash Traded Volume Ratio

To offer a representable analysis of wash trading activities among collections, it is suboptimal to compare the number of trades and the generated volume from them with each other. Some collections have more volume than others, which indicates their size and popularity. Therefore, it is essential to look at the ratio of wash traded volume and the total examined volume. This value is also shown on our website (see *Figure 4.2* references 4 and 5).

The share of wash traded volume shown in the following *Table 5.2* is calculated by dividing the volume of all detected wash trades from the received trades by the collections total volume. Because we considered the collections to have a large coverage of their total volume in our database, this value is representable for the entire volume of the collection.

Table 5.2: Wash Traded Volume Ratio

	NFT Collection	Total Volume	Wash Traded Share
1	Anime Cute Girl	1,539.10 SOL	95.46%
2	Bear Cleo Club	1,054.99 SOL	95.12%
3	Alien Worlds	249.77 SOL	91.27%
4	Bulldog Mafia	567.60 SOL	88.58%
5	SolTV	647.24 SOL	85.51%
6	Samuway	1,478.49 SOL	84.38%
7	Last Retronauts	1,450.45 SOL	82.82%
8	Wack Wack	2,572.26 SOL	78.73%
9	Eco Eyes	1,077.28 SOL	73.59%
10	Gothic Demon	499.77 SOL	70.40%
11	Degen Reptilian	312.62 SOL	59.66%
12	ABC Pirates	29.48 SOL	12.22 %
13	Trippin' Baby Ape Tribe	1,519.43 SOL	9.39%
14	BunnyToons	41.04 SOL	1.70%
15	Goblin Army	1,952.82 SOL	0.00%
16	Halo Gods	1,788.58 SOL	0.00%
17	Gyris: The Mara	426.21 SOL	0.00%
18	DooDoo	221.43 SOL	0.00%

Table 5.2 shows the wash traded volume ratio along with the total volumes in Solana. This first insight into the wash trading activities together with the trading volume shows that there is no correlation between the total volume of the collections and the portion of wash traded volume. We can see that the Collection Anime Cute Girl has the highest share of wash traded volume and has one of the highest total volumes. Instead, Alien Worlds has the third-highest share of wash trades but has the fourth-lowest total volume among the examined collections.

Taking into account the statistical data, we can determine, that Goblin Army is the most valuable NFT collection of the 18 as it has the most organically developed value. The collection ABC Pirates is the least valuable collection, because of its organically generated volume of only 25.88 SOL. The collection with a total volume above 1,000 SOL but with the least organic share is Bear Cleo Club, with only 47.86 SOL of real trading volume.

5.4 Suspicious Address Ratio

The community of an NFT collection is the most essential part of its success as mentioned in *Section 1.2*. Therefore, it is important to check the ratio of suspicious addresses and the total addresses who traded the tokens to be sure that only a few market participants faked the demand. This information is important for private investors to check if the community of the collection is trying to manipulate the market and, therefore not valuable for the collection.

Figure 5.1 examines the relation between the ratio of wash traders and the share of wash traded volume. The collections on the X-Axis are ordered the same as in *Table 5.1* and *Table 5.2*, so descending ordered by their wash traded share. On the Y-Axis, the shares of wash traders among all are shown, which is calculated by dividing the number of wash trades by the number of total trades among the transactions in our database. This value will be displayed in the bottom part of component 5, shown in *Figure 4.4* on our website.

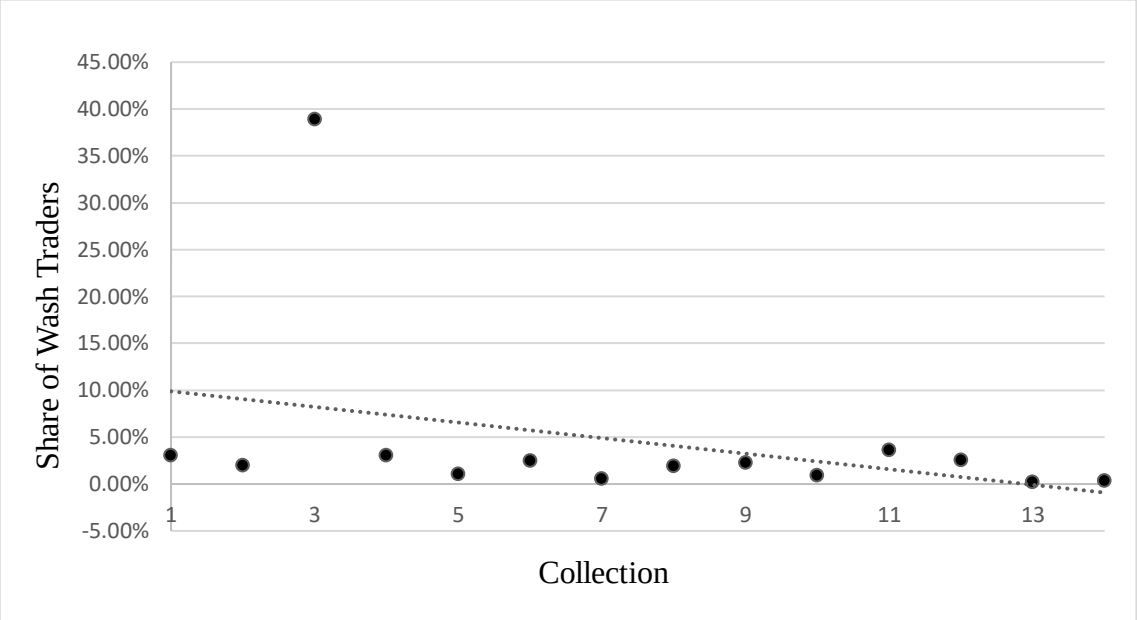


Figure 5.1: Suspicious Address Ratio of Collections sorted by Wash Traded Share

Looking at these results, it can be seen most wash trader portion is between 0% and 5%. This indicates that only a few addresses execute these malicious trades. There is also a clearly defined pattern in the chart by the decreasing trendline, illustrated by the dotted

line. The decreasing trend can be taken to mean that the lower the portion of wash trades is, the lower the share of wash traders.

Nevertheless, one can find a breakout of the rule in the collection Alien Worlds, which could be responsible for the drop in the trendline.

In *Figure 5.2*, this value is excluded to confirm the rule just defined.

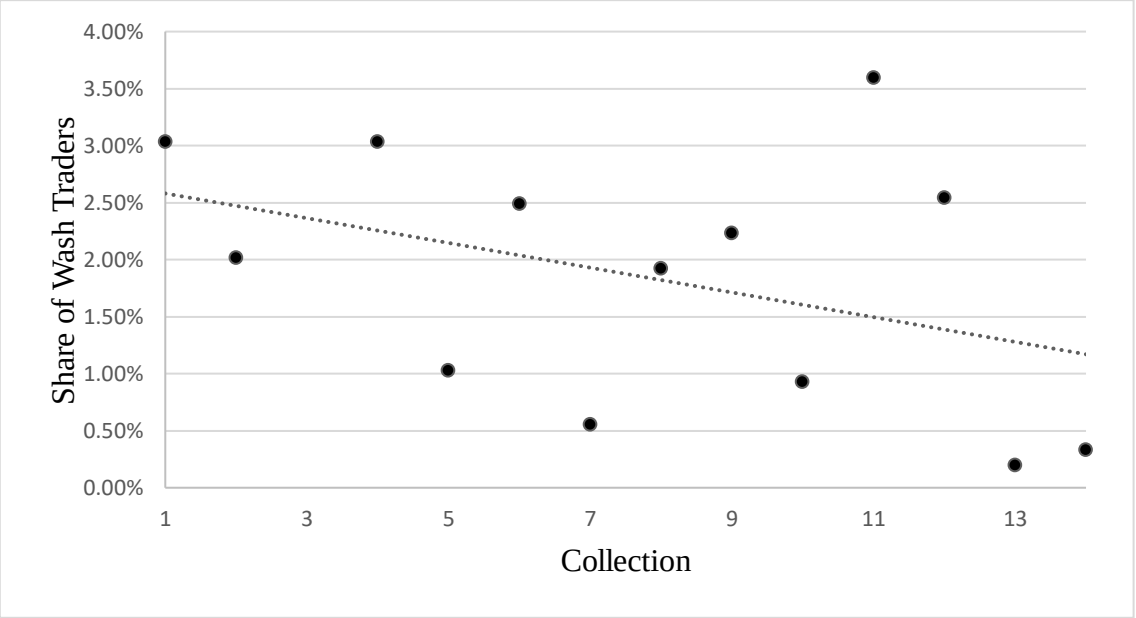


Figure 5.2: Suspicious Address Ratio of Collections without Collection 3 sorted by Wash Traded Share

The graph above proves the steady decrease in the trend, previously defined.

5.5 Marketplace Distribution of Wash Trades

The trading of NFTs can take place on many different Marketplaces on Solana. To have insight into which marketplace appears to have the most wash trading activities plays an impactful role in choosing the marketplace to trade on. Therefore, analysis of the distribution of all trades including wash trades will be made. Subsequently, this subsection will also look at how the largest platform Magic Eden tries to fight these malicious activities to protect investors from scams or similar.

The following *Figure 5.3* depicts the distribution among marketplaces of all inspected trades.

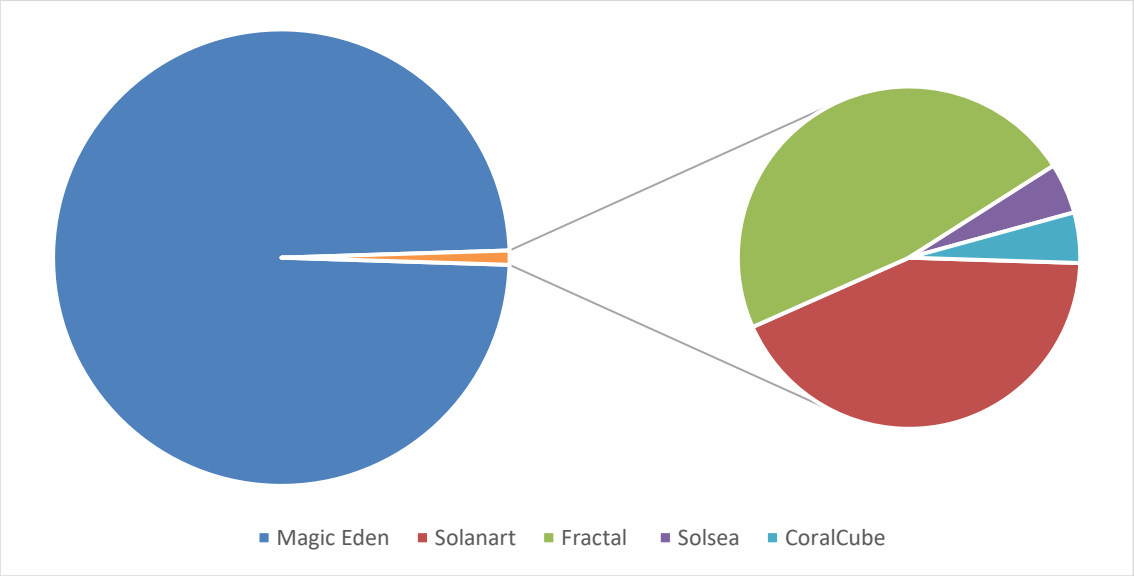


Figure 5.3: Distribution of all trades on Solana NFTMs

The investigation showed, that 99% of the examined trades were made on Magic Eden. From the rest 1%, 47.62% were executed on Fractal, 42.86% on Solanaart, 4.76% on SolSea, and 4.76% on CoralCube.

All discovered wash trades among the above transactions happened on Magic Eden. This can be reasoned by the increasing popularity of that marketplace, together with the small size of those collections, which is why not every Marketplace lists those collections.

To try to get rid of wash trades and other malicious activities, ME flags such collections on their website to warn any user that these collections are considered scams or have a significant portion of wash traded volume.

The following *Table 5.3* shows all collections on which our web app detects wash trade, along with if the collection is flagged by Magic Eden or not.

Table 5.3: Wash Traded Collections on ME

	NFT Collection	Wash Traded Share	Flagged by ME
1	Anime Cute Girl	95.46%	No
2	Bear Cleo Club	95,12%	Yes
3	Alien Worlds	91.27%	No
4	Bulldog Mafia	88.58%	No
5	SolTV	85.51%	No
6	Samuway	84.38%	Yes
7	Last Retronauts	82.82%	Yes
8	Wack Wack	78.73%	Yes
9	Eco Eyes	73.59%	No
10	Gothic Demon	70.40%	Yes
11	Degen Reptilian	59.66%	No
12	ABC Pirates	12.22%	No
13	Trippin' Baby Ape Tribe	9.39%	No
14	BunnyToons	1.70%	Yes

The ratio of collections, that are flagged and those that are not, is 8:6 and therefore not optimal for protecting users. Collections with a high percentage of wash trading are only sometimes flagged by Magic Eden, as can be seen in Anime Cute Girl and Alien Worlds. Collections that can be declared as critical, according to their wash traded share (> 70%) are only flagged by 50%. But collections with a share below 70% are flagged by 25%.

In this analysis, it is important to keep in mind that ME's flagging does not only refer to wash trading. Therefore, collections such as Bunny Toons are also flagged with a wash traded percentage of 1.7%, as these collections may otherwise pose a threat to collectors. We can see then that Magic Eden is trying to provide good coverage among these critical collections, but this is insufficient.

6 Conclusion

In this work, we have dealt with the development of a website to check wash trading activities on NFT collections on the Solana Blockchain. We also used this website to perform additional analysis on specific collections and check how the largest marketplace ME is acting against this manipulation and how effective this is.

To do this, we first outlined the problem of wash trading and went into more detail about the dangers that come with it. Due to the artificially increased trading volume of these collections, investors can run the risk of putting money into a project that is less popular than it seems. In the worst case, this can lead to a total loss of the invested capital.

Therefore, providing users with a user-friendly way to learn about these activities in collections is essential. For this purpose, our website provides valuable information, such as the marketplace distribution of wash trades and the number of traders who have executed them. Also, the possibility to query wash trades of a specific token and check if it has been used for such an activity is essential in this context. In order to provide these functions, we have developed an algorithm that searches for SCCs in a graph representing all transactions and counts them to see if they are repeated too often and can therefore be declared as wash trades. In the course of the analysis, we checked this algorithm with the help of a third party to see if it correctly identified wash trades. This analysis showed that our algorithm correctly identifies wash trades 87.5% of the time. When identifying collections without wash trades, our algorithm was 100% correct. Due to these high hit rates, the website can be an important first aid in selecting an investment in an NFT collection.

By performing different analyses on 18 NFT collections with a small trading volume, we could show that, on the one hand, the size of a collection measured by the volume does not influence the wash trading share. On the other hand, it was found that these wash trades were performed by an average of about 4% of the total traders. Furthermore, we found a decreasing trend of this share in correlation with the decreasing portion of wash traded volume of the collections.

Our analysis of the effectiveness of flagging suspicious collections by the ME platform showed that only 50% of collections with a wash traded share of 70 % are flagged. This

means that despite this measure, there is still too high a risk for individuals to lose their invested capital.

7 Future Work

The issues raised in *Section 4.2* have greatly limited the development of the website. If the problems at Magic Eden are solved soon, we can consider implementing some features. The long loading time due to the complex calculations of the used algorithm could be outsourced to some extent by only executing them when a collection is searched for the first time. One idea to keep updating the wash trade statistic would be to implement an automatic update of the data on the server. This would make a request to ME in a two-week interval to check if there are new sales and request them and include them in the calculation. This would provide the user with up-to-date information, which is currently not the case, as mentioned in *Section 4.1.2*.

It is also essential to have wide coverage of collections in our system, which this automatic program could handle. This would be advantageous for a shorter loading time of the collections.

To obtain even more accurate results in the calculation of wash trading activities, it would be useful to implement a method like Hello Moon uses, which was mentioned in *Section 3.3*. This could reduce the detection of randomly strongly linked components.

In order to address a broader audience, one can also consider offering analytics for other blockchains, such as Ethereum or Cardano.

What is not covered in the current version of the website is the timing of sales. That would be helpful to understand if SCC considered as wash trading is not, because of the high time difference between the trades. We could implement a menu where a period from which you want to see the trades or wash trades can be specified.

Furthermore, The actual analysis mentioned in *Section 5* could be done as soon as the bug in the ME API is solved. To confirm the relations found in this paper also for collections of larger sizes, one can perform similar analyses as in this paper. This would provide a great extension to the knowledge of wash trading activities. These results can then be compared with the HMWT index and the results obtained for collections of similar size on other blockchains such as Ethereum.

List of Figures

List of Tables

Bibliography

[1] "Non-fungible tokens (NFT)," Ethereum, [Online]. Available: https://ethereum.org/en/nft/. [Accessed 15 November 2022].

[2] Business Punk Redaktion , "25 Milliarden Dollar Umsatz mit NFTs im Jahr 2021," Business Punk, 12 Januar 2022. [Online]. Available: https://www.business-punk.com/2022/01/25-milliarden-dollar-umsatz-mit-nfts-im-jahr-2021/. [Accessed 15 November 2022].

[3] "NFT-Umsatz minus 80%," NEWSFLASH, 24 June 2022. [Online]. Available: https://www.profifoto.de/szene/notizen/2022/06/24/nft-umsatz-minus-80/. [Accessed 15 November 2022].

[4] "Top Sales by Ether Value," CryptoPunks, [Online]. Available: https://cryptopunks.app/cryptopunks/topsales. [Accessed 15 November 2022].

[5] K. J. Brooks, "Nike's new NFT sneakers selling for more than $100,000," CBS News, 28 April 2022. [Online]. Available: https://www.cbsnews.com/news/nike-cryptokicks-nft-blockchain-metaverse-rtfkt/. [Accessed 15 November 2022].

[6] M. Hainz, "Adidas Originals geht ins Metaverse: Die wichtigsten News zu den NFTs," GQ, 20 December 2021. [Online]. Available: https://www.gq-magazin.de/mode/artikel/adidas-originals-geht-ins-metaverse-die-wichtigsten-news-nfts. [Accessed 15 November 2022].

[7] Chris, "Quartz: Ubisoft verkauft Ingame-Items jetzt auch als NFTs," tech rush, 9 December 2021. [Online]. Available: https://techrush.de/quartz-ubisoft-verkauft-ingame-items-jetzt-auch-als-nfts/?cookie-state-change=1668552130219. [Accessed 15 November 2022].

[8] Reeds Solicitors , "Are Non-Fungible Tokens Legally Regulated?," Lexology, 30 August 2022. [Online]. Available: https://www.lexology.com/library/detail.aspx?g=abdac300-8b09-40d2-853d-98a0db241fb2#:~:text=Under%20US%20securities%20law%2C%20for,its%20individual%20characteristics%20and%20features.. [Accessed 22 November 2022].

[9] "CIRCLE OF BRILLIANCE," Nasty Nerds, 2021. [Online]. Available: https://cob.nastynerds.io/. [Accessed 15 November 2022].

[10] "Nasty Nerds," Magic Eden, [Online]. Available: https://magiceden.io/marketplace/nasty_nerds. [Accessed 15 November 2022].

[11] buildooors, "SCB: Seriously… How Fast Can Solana Blockchain Get?," SOLANA BUILDOOORS, 25 April 2022. [Online]. Available: https://solana.blog/seriously-how-fast-can-solana-blockchain-get/. [Accessed 15 November 2022].

[12] "Is Solana Decentralized? Outages, VC Ties and More Worries," BYBIT, July 6 2022. [Online]. Available: https://learn.bybit.com/deep-dive/is-solana-decentralized/. [Accessed 15 November 2022].

[13] B. Becher, "What Is Layer 1 in Blockchain?," builtin, 1 November 2022. [Online]. Available: https://builtin.com/blockchain/layer-1-blockchain. [Accessed 21 November 2022].

[14] A. Yakovenko, "Solana," November 2017. [Online]. Available: https://solana.com/solana-whitepaper.pdf. [Accessed 15 November 2022].

[15] Solana Explorer Beta, [Online]. Available: https://explorer.solana.com/. [Accessed 15 November 2022].

[16] "The Ethereum Blockchain Explorer," Etherscan, [Online]. Available: https://etherscan.io/. [Accessed 15 November 2022].

[17] Blockchain.com, [Online]. Available: https://www.blockchain.com/explorer. [Accessed 15 November 2022].

[18] O. Solberg, "How Much Are Solana Fees?," SOLBERG INVEST, 17 June 2017. [Online]. Available: https://solberginvest.com/blog/how-much-are-solana-fees/. [Accessed 15 November 2022].

[19] "Ethereum Average Gas Price," YCHARTS, [Online]. Available: https://ycharts.com/indicators/ethereum_average_gas_price#:~:text=Basic%20Info,85.19%25%20from%20one%20year%20ago.. [Accessed 15 November 2022].

[20] Real Vision, "How to Create a Smart Contract on Ethereum," Real Vision, 15 June 2022. [Online]. Available: https://www.realvision.com/blog/how-to-create-a-smart-contract-on-ethereum#:~:text=According%20to%20Yahoo%20Finance%2C%20the,developers%20to%20create%20smart%20contracts.. [Accessed 21 November 2022].

[21] A. Yakovenko, "Sealevel — Parallel Processing Thousands of Smart Contracts," Medium, 9 September 2019. [Online]. Available: https://medium.com/solana-labs/sealevel-parallel-processing-thousands-of-smart-contracts-d814b378192. [Accessed 15 November 2022].

[22] "Introduction," Metaplex, 6 November 2022. [Online]. Available: https://docs.metaplex.com/. [Accessed 15 November 2022].

[23] "Program Derived Addresses (PDAs)," Solana Cookbook, 18 August 2022. [Online]. Available: https://solanacookbook.com/core-concepts/pdas.html#facts. [Accessed 30 November 2022].

[24] "Token Metadata Overview," Metaplex, 6 November 2022. [Online]. Available: https://docs.metaplex.com/programs/token-metadata/overview. [Accessed 15 November 2022].

[25] OpenSea, „Retrieve Assets,“ OpenSea, July 2022. [Online]. Available: https://docs.opensea.io/reference/getting-assets. [Zugriff am 15 November 2022].

[26] Paul, "Programming on Solana - An Introduction," paulx, 14 January 2021. [Online]. Available: https://paulx.dev/blog/2021/01/14/programming-on-solana-an-introduction/#intro-motivation. [Accessed 15 November 2022].

[27] "What is Auction House," Metaplex, 6 November 2022. [Online]. Available: https://docs.metaplex.com/programs/auction-house/overview. [Accessed 15 November 2022].

[28] MagicEden, "We Always Ship: March," MagicEden, 2 April 2022. [Online]. Available: https://blog.magiceden.io/we-always-ship-march-magic-eden. [Accessed 15 November 2022].

[29] J. Chen, "Wash Trading: What It Is and How It Works, With Examples," Investopedia, 30 September 2022. [Online]. Available: https://www.investopedia.com/terms/w/washtrading.asp. [Accessed 15 November 2022].

[30] M. Huillet, "Bitwise: 95 Prozent des Volumens an unregulierten Kryptobörsen verdächtig," Cointelegraph, 23 March 2019. [Online]. Available: https://de.cointelegraph.com/news/bitwise-tells-us-sec-that-95-of-volume-on-unregulated-crypto-exchanges-is-suspect. [Accessed 16 November 2022].

[31] SEC, "Securities and Exchange Commission," 25 September 1997. [Online]. Available: https://www.sec.gov/litigation/admin/3439133.txt. [Accessed 15 November 2022].

[32] H. Kumar, "Squid Token Crashes: Investors Lose over $3 Million, Token Value Near-Zero," Outlook, 2 November 2021. [Online]. Available: https://www.outlookindia.com/website/story/business-news-squid-token-crashes-investors-lose-over-3-million-token-value-near-zero/399582. [Accessed 16 November 2022].

[33] "Squid Game Coin Collapsed– How to Avoid Cryptocurrency Scams," KuCoin, 5 November 2021. [Online]. Available: https://www.kucoin.com/de/blog/squid-game-coin-collapsed-how-to-avoid-cryptocurrency-scams. [Accessed 16 November 2022].

[34] TokenInsights, "Many Exchanges Continue to Engage in Wash Trading, Wash Trading Research (Full Version) Shows," Medium, 31 October 2019. [Online]. Available: https://tokeninsight.medium.com/many-exchanges-continue-to-engage-in-wash-trading-wash-trading-research-full-version-shows-1fb26742f7ee. [Accessed 18 November 2022].

[35] "What is market liquidity and why is it important?," IG, [Online]. Available: https://www.ig.com/en/trading-strategies/what-is-market-liquidity-and-why-is-it-important--190214#:~:text=Why%20is%20market%20liquidity%20so%20important?. [Accessed 16 November 2022].

[36] "NFT Money Laundering: What You Need to Know," Comply Advantage, 26 July 2022. [Online]. Available: https://complyadvantage.com/insights/nft-money-laundering-what-you-need-to-know/. [Accessed 16 November 2022].

[37] NFTGators, Twitter, 21 August 2022. [Online]. Available: https://twitter.com/NFTgators/status/1561258837348417537. [Accessed 16 November 2022].

[38] "NFT Marketplaces," DappRadar, [Online]. Available: https://dappradar.com/nft/marketplaces. [Accessed 16 November 2022].

[39] djemba6, "X2Y2 Trades," Dune, [Online]. Available: https://dune.com/djemba6/x2y2-trades. [Accessed 16 November 2022].

[40] HelloMoon, [Online]. Available: https://www.hellomoon.io/nft/eco-eyes/washtrading. [Accessed 19 November 2022].

[41] Carnegie Mellon University, "Lecture #19: Depth First Search and Strong Components," 1 November 2018. [Online]. Available: https://www.cs.cmu.edu/~15451-f18/lectures/lec19-DFS-strong-components.pdf. [Accessed 16 November 2022].