NFTeller: Dual-centric Visual Analytics for Assessing Market Performance of NFT Collectibles

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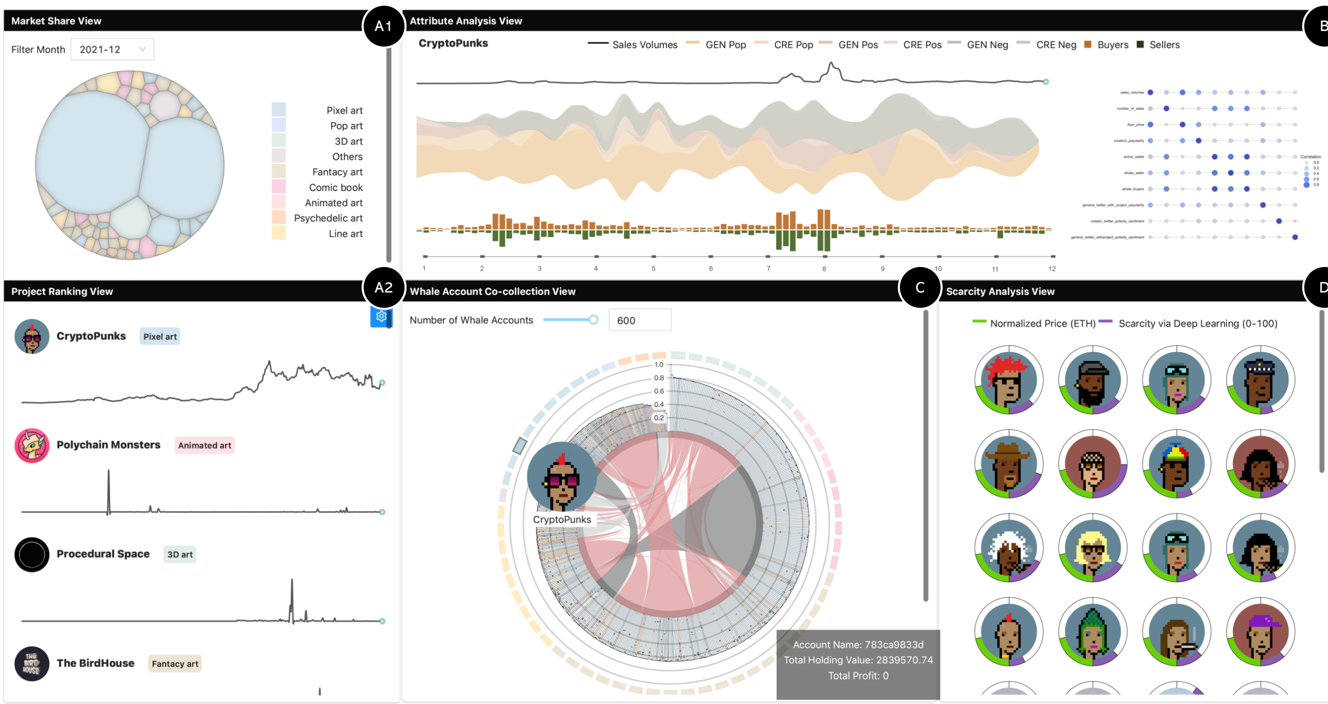

Figure 1: Interface of *NFTeller*: i) the *Market Share View* (A1), *Project Ranking View* (A2) and *Attribute Analysis View* (B) display the evolution of NFT marketplaces and individual projects from multi-faceted perspectives; ii) the *Whale Account Co-collection View* (C) and *Scarcity Analysis View* (D) illustrate the co-collection preference of whale accounts.

ABSTRACT

Non-fungible tokens (NFTs) have recently gained widespread popularity as an alternative investment. However, the lack of assessment criteria has caused intense volatility in NFT marketplaces. Identifying attributes impacting the market performance of NFT collectibles is crucial but challenging due to the massive amount of heterogeneous and multi-modal data in NFT transactions, e.g., social media texts, numerical trading data, and images. To address this challenge, we introduce an interactive dual-centric visual analytics system, *NFTeller*, to facilitate users' analysis. First, we collaborate with five domain experts to distill static and dynamic impact attributes and collect relevant data. Next, we derive six analysis tasks and develop *NFTeller* to present the evolution of NFT transactions and correlate NFTs' market performance with impact attributes. Notably, we create an augmented chord diagram with a radial stacked bar

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chart to explore intersections between NFT collection projects and whale accounts. Finally, we conduct three case studies and interview domain experts to evaluate the effectiveness and usability of this system. As such, we gain in-depth insights into assessing NFT collectibles and detecting opportune moments for investment.

CCS CONCEPTS

• **Information systems → Data analytics**.

KEYWORDS

Non-fungible tokens (NFTs), Blockchain, Visual analytics

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1 INTRODUCTION

Since mid-2021, non-fungible tokens (NFTs) have attracted more and more people. In brief, NFTs are non-interchangeable units of data stored on the blockchain, which can bind with any kind of asset and certify its authenticity, scarcity, and copyright [2]. These NFT-tied assets are mostly transacted in NFT marketplaces (e.g., OpenSea [20] and SuperRare [11]) with crypto wallets. Among them, NFT collectibles have emerged as the most popular category, capturing a significant market share while generating a lot of buzz and engagement on social media (e.g., Twitter and Discord). Specifically, NFT collectibles are NFTs with financial and aesthetic value to be collected, mostly taking the form of profile pictures and digital art. Nevertheless, the lack of assessment criteria has hindered participants from making informed investment decisions, which could result in financial loss and impede NFT marketplaces from achieving healthy development. Thus, intuitive analytics tools that facilitate participants to assess NFT collectibles are in demand.

Despite increasing studies assessing NFTs, the focus has been on utilizing machine learning to model NFT transaction data [11, 18]. However, this approach lacks interactivity and transparency in attribute selection, which can be challenging for individuals without data mining expertise to understand. Thus, a visual analytics method following a user-centered design protocol could be applied to address this issue. Moreover, previous visual analytics (VA) systems for blockchain data mainly focus on detecting cryptocurrency transaction patterns from single-entity perspectives (e.g., exchanges, mining pools, and accounts) [13, 16, 23]. Hence extant designs can neither adapt to heterogeneous multi-modal NFT transaction data nor present bipartite set-relation between NFT projects and collectors, particularly influential whale accounts.

To bridge this research gap, we propose an interactive visualization system to flexibly fulfill NFT assessment for target users (i.e., investors, collectors, and brokers in NFT marketplaces) to analyze. Nevertheless, we encounter three challenges when employing *NFTeller*: 1) Extract attributes that impact the market performance of NFT collectibles from various potential variables; 2) Intuitively present the intersections between NFT collection projects and whale accounts; 3) Provide dual-centric interactive exploration so target users can flexibly assess NFT collectibles. To address the first challenge, we collaborate with domain experts to identify **static** and **dynamic** attributes that mostly impact NFTs' market performance. For the second challenge, we leverage an augmented chord diagram with a radial stacked bar chart to depict the set relations between whale accounts and NFT projects. To tackle the third challenge, we develop a VA system, *NFTeller* (Fig. 1), with five well-coordinated views. The *Market Share View* (Fig. 1 A1), *Project Ranking View* (Fig. 1 A2), and *Attribute Analysis View* (Fig. 1 B) display the evolution of 61 NFT collection projects and provide correlation analysis between impact attributes and market performance. The *Whale Account Co-collection View* (Fig. 1 C) and *Scarcity Analysis View* (Fig. 1 D) depict co-occurring whale accounts of NFT collection projects and co-collected NFT collectibles with scarcity degree presented. The main contributions of this paper are as follows:

- An interactive visual analytics system, *NFTeller*, allows users to explore, analyze, and evaluate NFT collectibles.
- A novel design of an augmented chord diagram to fulfill dual-centric analysis of NFT transactions.
- In-depth insights into NFT collectibles through evaluation of three case studies and interviews with domain experts.

Table 1: Definitions of concepts for assessing NFT collectibles.

Key concepts	Definition
NFT Collectibles	Visual digital art that is cryptographically registered with a token on a blockchain.
NFT Collection Projects	A series of similar-styled NFT collectibles launched by artists or creators.
Whale Accounts	Individuals or entities that hold large amounts of cryptocurrencies.
Impact Attributes	Static and dynamic characteristics of NFTs influencing market performances.

2 RELATED WORK

We introduce key concepts (see Tab. 1) and related works as follows:

NFT Assessment Analysis. An NFT is "*a cryptographically unique, indivisible, irreplaceable and verifiable token*" [17], which are minted and verified automatically by pre-specified smart contracts. Unlike fungible tokens, such as cryptocurrencies, each NFT is one-of-a-kind and non-interchangeable. Among various NFTs, NFT collectibles tied with creative content (e.g., digital art, music, and videos) have gone viral in recent years as an alternative investment [7]. Nevertheless, the lack of assessment criteria and diverse potential impact attributes have created challenges for investors and collectors to make informed decisions.

The challenges have raised research enthusiasm for *NFT Assessment Analysis*, which consists of two main branches: 1) *modeling NFT transactions* [11, 19] and 2) *correlating communication effects with NFT market performance* [6, 21]. For instance, Wen et al. detected wash trading activities in NFT marketplaces by monitoring the transaction flow among crypto wallet addresses [19]. Meanwhile, several studies have scrutinized the correlation between NFT communities and their sway over NFT valuation by exploring how communication effects impact NFT market performance. Respectively, Kapoor et al. and Wilkoff et al. observed that social media popularity and media reports could affect the liquidity and price of

Table 2: Mapping visual design of *NFTeller* from static and dynamic impact attributes, data, analysis tasks, and system views.

Impact Attributes				Tasks	Views	Dataset
Static	Visual Features	· Style Category	· The aesthetic style of NFT collection projects.	T5, T6	A1, C	VFD
		· Visual Scarcity	· The degree of uniqueness of NFT collectibles' visual features within a collection.	T4, T6	A1, D	
Dynamic	Communication Effects	· Popularity	· The attention of NFT projects get on social media.	T1, T2, T3	B	CED
		· Sentiment Polarity	· The negative and positive sentiments of discussions about NFT collection projects.	T1, T2	B	
Dynamic	Whale Accounts' Behaviors	· Transaction Activities	· Transaction activities of NFT collectibles among whale accounts.	T1, T2, T3, T5	B, C, D	WBD
		· Co-collection Preference	· Co-collected NFT collectibles of certain group of whale accounts.	T1, T2, T4, T6	C, D	

NFTs [6, 21]. Nevertheless, these studies only provide the statistical outputs of machine learning or deep learning models, which are inadequate for users to understand. To this end, we collaborate with NFT domain experts to identify impact attributes for analysis.

Blockchain Data Visual Analytics. The visualization community has a rich history of analyzing blockchain data [15], which primarily focuses on 1) *detecting transaction patterns* [8, 24] and 2) *activities of entities* (i.e., individuals and commercial institutions) [13] in cryptocurrency markets. However, NFTs are distinguished from cryptocurrencies in the heterogeneous multi-modal data structure (e.g., visual images and social media texts). Thus, current VA systems for exploring blockchain data cannot be directly adapted to NFT assessment tasks. Moreover, most extant VA systems facilitate analyzing cryptocurrency transactions from a single-entity perspective, such as mining pools [16, 22], exchanges [23], and individual accounts [13]. Therefore, their visual designs and workflows are limited to illustrating the bipartite set relations between NFT collection projects and whale accounts. To bridge this research gap, we created an augmented chord diagram and integrated a flexible workflow to satisfy dual-centric analysis.

3 DATA AND TASKS ABSTRACTION

3.1 Data Abstraction

We conducted semi-structured interviews with five domain experts (E_{A}–$_{E}$) and applied thematic analysis to identify impact attributes and data required for analysis (see demographics in Appendix I).

3.1.1 Attributes Identification. Based on workflows described by domain experts (see examples in Appendix II) and influential factors mentioned by extant literature [6, 11, 12], we propose a comprehensive impact attributes framework for NFT assessment (Tab. 2), which involves one static and two dynamic impact attributes. Particularly, the *static* **visual features** determine the aesthetic style category and scarcity degree of individual NFT collectibles [9, 10]; the *dynamic* **communication effects** [1] involves social media popularity and sentiment polarity of participants' discussions about NFT projects; while the *dynamic* **whale account behaviors** [12] consists of their transaction activities and preferred co-collected NFT collection projects. Moreover, we discuss with domain experts about the sampling criteria and select 61 top-ranking NFT collection projects and 600 active whale accounts.

3.1.2 Data Description. According to the aforesaid sampling targets, we construct three heterogeneous multi-modal datasets (Fig. 2 A). We apply a web crawler and API acquisition to collect data from three resources: Twitter, OpenSea, and NFTGO [12]. The data wrangling processing is based on Python in macOS version 12.0.1 and is transformed into numerical tabular data.

Visual Feature Data (VFD) comprises 281,142 images of NFT collectibles from 61 projects. Through collaboration with a digital artist, we manually labeled the aesthetic style of each project. We identified nine categories, i.e., fantasy art, line art, pixel art, 3D art, comic book art, psychedelic art, pop art, animated art, and others (see Appendix III). In addition, we also gather temporal market performance data of NFT projects, including sales volume, number of sales, timestamps, and floor price in 2021 (Jan.1 - Dec.31).

Whale Behavior Data (WBD) depicts the transaction and collection records of 600 whale accounts gathered from NFTGO. WBD includes whale accounts' holding values, profits and losses, and the number of holding NFTs. We also collect transaction metadata, such as token IDs, traders' addresses, and timestamps. We categorize the data into a 1-to-N structure by indexing unique whale account addresses to detect co-collection behaviors (see Fig. 2 B2).

Communication Effects Data (CED) describes the popularity and sentiment polarity of NFT collection projects on Twitter. We separately translate, compile, and consolidate daily textual Tweets from the general public and NFT influencers throughout 2021 to monitor market operations (refer to Fig. 2 B1).

3.2 Task Analysis

We iteratively condensed six tasks into three categories according to our domain experts' requirements:

Two **General-Market-Level** questions uncover the evolution and dynamic impact attributes on NFT market performance.

T1. *How do transaction patterns of overall NFT marketplaces evolve?* Transaction patterns indicate the market performance evolution of NFT collection projects. Thus, identifying these patterns can assist users in making informed investment decisions.

T2. *How do dynamic impact attributes correlate with NFT marketplaces' evolution?* Dynamic attributes can fluctuate NFT market performance. Therefore, exploring the correlation between these attributes and NFT transaction patterns is essential.

Two **Project-Centric-Perspective** questions evaluate NFT collection projects and compare NFT collectibles.

T3. *How do different impact attributes influence the development of individual NFT collection projects over time?* How does the market performance of individual NFT collection projects evolve? Do NFT collection projects with more attention on social media and attracting more whale accounts perform better?

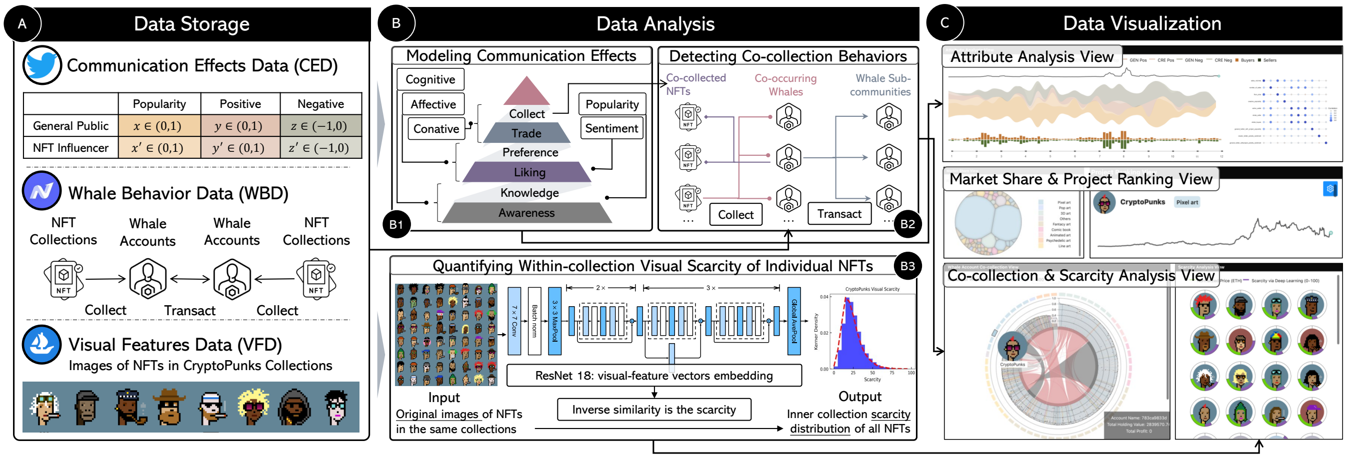

Figure 2: System Overview. *NFTeller* includes three modules: (A) Data storage; (B) Data processing; (C) Data visualization.

T4. *How does the "scarcity" degree imply unique NFT collectibles otherwise neglected?* Enabling a direct comparison between price and scarcity degree could identify underestimated and overestimated NFT collectibles.

Two **Whale account-Centric-Perspective** questions reveal the co-collection and transaction patterns of whale accounts.

T5. *What is the pattern of whale accounts' transaction behaviors?* The ratio of whale accounts to total holders is an essential indicator for the prospects of NFT collection projects. Further, co-occurring whale accounts and their sub-communities can greatly impact project credibility.

T6. *What are the similarities and differences among individual whale accounts' co-collections?* Profits and losses differentiate individual whale accounts. Thus, comparing their co-collection preference could provide more specific insights for target users.

4 DATA ANALYSIS

4.1 Modeling Communication Effects

The valuation for NFT-tied assets is a social phenomenon involving marketing schemes and the recognition of participants (Fig. 2 B1). This is reflected by the popularity (i.e., cognition) and sentiment polarity (i.e., affection) of NFT-related topics on social media [6].

4.1.1 Quantifying Social Media Popularity. Regarding defining the popularity on Twitter, we collect the daily tweet corresponding to the 61 projects as illustrated in **CED**. For reorganizing Twitter data, we demonstrate the empirical popularity definition [14]. As such, the underlying factors for measuring popularity involve the number of tweets, likes, comments, and retweets. The equation for calculating the value of popularity $Po(t)$ is shown as

$$Po(t) = [(w_1 fc(t) + w_2 rc(t) + w_3 pc(t)]w_4, \tag{1}$$

where $0 < t \leq T$, and w1, w2, w3, and w4 respectively indicate the number of tweets, likes, comments, and retweets. They generally represent how much attention individual NFT collection projects have received. Inspired by Kapoor et al. [6], we currently assign identical weights for w1, w2, w3, and w4, as these four characteristics are equally significant for NFT social media popularity.

4.1.2 Unsupervised Sentiment Analysis of Social Media. Since the collected Twitter dataset is unlabeled, we consider applying an unsupervised dictionary-based text analysis approach to process the substantial text data. Therefore, we illustrate the social media sentiment scores using the well-defined TextBlob technique [14]:

$$t_i = \sum_{m=1}^{M} \frac{S_m W_{im}}{N_i}. \tag{2}$$

We select the TextBlob dictionary method for two reasons: TextBlob can deal with relatively chaotic raw data; it provides clear triple results to present positive, neutral, and negative sentiment outcomes. In comparison, algorithms like VADER [4] rely heavily on the quality of text data and are affected by special symbol issues, which could cause a positive bias in the generated sentiment distributions.

4.2 Artificial Scarcity of NFT Collectibles

The term "scarcity" in the context of NFT collectibles pertains to the degree of uniqueness exhibited by an individual NFT within a collection with respect to its visual features [10]. NFTs that demonstrate greater diversity in their visual features are generally more distinguishable and highly valued. However, quantifying NFT scarcity has proven to be a non-trivial problem. Various commercial analytics tools calculate scarcity scores for individual NFTs by evaluating the proportion of labeled visual traits [9] or normalizing the sum of reciprocal and Jaccard similarity [5]. Nevertheless, these methods often rely on predefined labels and may overlook critical latent information. In light of this, we propose an automatic approach for assessing scarcity, expressed as $Scarcity = 1 - Similarity$, which ranges from 0 to 100.

$$\cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}, \tag{3}$$

$$Scarcity = 100 * \frac{(1-\cos(\theta)) - \min(1-\cos(\theta))}{\max(1-\cos(\theta)) - \min(1-\cos(\theta))}. \tag{4}$$

We calculate artificial scarcity through four steps: deep residual learning [3], feature embedding, cosine similarity calculating, and modified Min-Max Normalization (Fig. 2 B3). The first step is to train with every NFT collectible image on a collection basis using ResNet-18. We train 61 NFT projects respectively, each with 1000 to

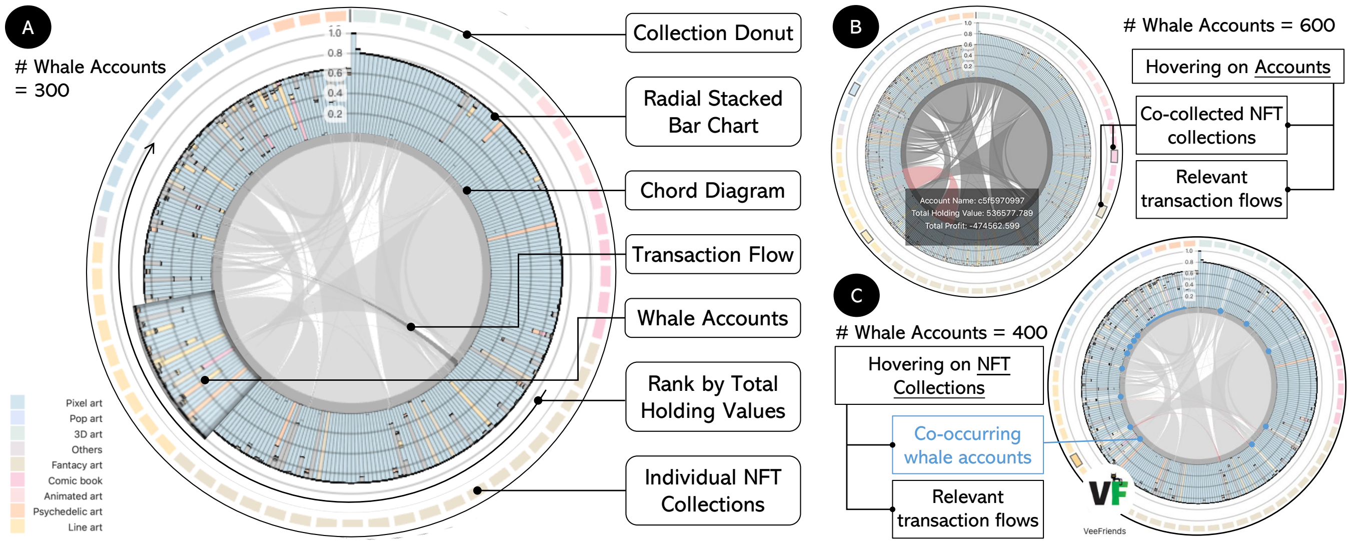

Figure 3: (A) Visual design of dual-centric whale account co-collection view. (B) Hovering on accounts shows co-collected NFT collections and transaction flows; (C) Hovering on NFT collections shows co-occurring accounts and transaction flows.

10000 images. The second step separately extracts 512-dimensional feature vectors from NFT collectible images per collection by the pre-trained ResNet-18. The Min-Max normalization (4) is then applied to the within-collection cosine similarity of images to re-rank the inner collection scarcity distribution (3), where A and B are representative vectors of NFT image items and n represents the aforesaid 512-dimensional feature vector.

5 VISUAL DESIGN

We follow user-centric principles to direct the design process: (a) We derive analysis tasks and design requirements of target users (Sec. 3). (b) We prototype and present the system to them to get responses for iteration. As such, we develop dual-centric analysis workflows to facilitate flexible interactions and create novel designs to intuitively illustrate impact attributes (Fig. 2 C). (c) We implement the VA system to satisfy analysis from multi-faceted perspectives.

5.1 Illustration of NFT Projects' Evolution

5.1.1 Market Share View. The *Market Share View* (Fig. 1 A1) is a Voronoi treemap presenting the aesthetic style categories and the evolving market share of NFT collection projects (**T1**).

We aggregate NFT collection projects based on their shared aesthetic categories. We then partition these categories into smaller cells using weighted sales volumes of the included projects, allowing users to quantify the market share in current NFT marketplaces. Users can view and compare the growth of different style categories of NFT collection projects by filtering this data by month. To enhance the user experience, we employ a unified color map to represent each aesthetic style category, as illustrated in Fig. 3 A.

5.1.2 Project Ranking View. The *Project Ranking View* (Fig. 1 A2) is a series of vertically aligned line charts for users to observe and compare the evolution of individual NFT collection projects efficiently (**T1**). Domain experts regard the floor price of NFT collection projects as a specific indicator of market performance. Thus, we intuitively present them by ordered line charts. Users can sort the NFT collection projects in descending order according to their latest sales volume, floor price, and the number of sales.

5.1.3 Attribute Analysis View. The *Attribute Analysis View* (Fig. 1 B) illustrates the market performance and dynamic impact attribute evolution for both NFT marketplaces (**T1**) and individual NFT collection projects (**T3**). With this view, users can easily evaluate NFT marketplaces and specific NFT collection projects and identify relevant dynamic impact attributes (**T2, T3**).

Description: The *Attribute Analysis View* (Figure 1 B) is structured into two regions. The lefthand side region contains three visualizations: a line chart, a ThemeRiver graph, and a bidirectional bar chart, all arranged vertically and synchronously depicting the timeline of 2021. The line chart portrays the sales volume progression of the entire NFT market by default and facilitates the selection of a specific project. The modified ThemeRiver graph illustrates the communication effects of *popularity* (in yellow), as defined in equation (1), and *sentiment polarity* on Twitter (positive sentiment in pink and negative sentiment in green), as defined in equation (2). Moreover, ThemeRiver employs hierarchical arrangements based on two entities, namely, NFT influencers and the general public, distinguished by saturation. Additionally, the bidirectional bar chart presents the frequency of whale accounts' "buying" (in orange) and "selling" (in dark green) behaviors. Meanwhile, the righthand side region displays correlation coefficients via a heat map matrix. This matrix comprises proportionate circles featuring a divergent color scheme allowing users to identify the impact degree of dynamic attributes on NFT market performance quickly.

Justification: We considered using a parallel coordinate chart and scatter plot to encode the temporal patterns of impact attributes. However, domain experts found these methods could be misleading and less precise, for they may induce visual clutter.

5.2 Whale Account Co-collection View

The *Whale Account Co-collection View* (Fig. 1 C) is an augmented chord diagram with a radial stacked bar chart, which illustrates the set relations between NFT collection projects and whale accounts. By exploring intersections, users can identify co-collected projects and co-occurring whale accounts, providing insights into their collection preferences (**T6**). Users can also investigate possible whale sub-communities through transaction patterns (**T5**).

Description: The *Whale Account Co-collection View* (Fig. 3) consists of three layers: the outermost donut, the middle radial stacked bar chart, and the innermost chord diagram to display the set relations between NFT collection projects and whale accounts. The outermost donut represents all NFT collection projects by 61 equally divided arcs encoded by the palette of aesthetic categories (Fig. 3 A). Upon hovering over a project, its corresponding logo and name are displayed (Fig. 3 C). The middle radial stacked bar chart ranks 600 whale accounts in terms of their total holding values, depicted by varying heights. The stacked bars within each account represent the holding values of NFT projects belonging to different aesthetic categories using the same color scheme. Users can manipulate the number of displayed whale accounts and retrieve associated information, such as wallet address and holding values, by hovering over the stacked bars (Fig. 3 B). The innermost chord diagram visualizes transaction flows between whale accounts. Binary flows connect the end of stacked bars representing "buying" and "selling" activities, with flow thickness proportional to transaction frequencies (Fig. 2 B2). This view supports dual-centric interactions from projects' and whale accounts' perspectives. By selecting NFT collection projects, all co-occurring whale accounts will be highlighted, with the transaction flows among them emphasized. Likewise, when a specific whale account is selected, all co-collected projects and related transaction flows receive attention.

Justification: We discussed with domain experts about alternative set-relation visualizations, such as a Sankey Diagram and an enhanced node-link diagram [25]. However, given the limited pixel space, these designs could encounter scalability or clutter issues, and the transaction details and sub-communities are hard to detect.

5.3 Scarcity Analysis View

The *Scarcity Analysis View* (Fig. 1 D) displays glyphs of NFT collectibles and their transaction history. This view facilitates analyzing scarcity patterns of whale account collections (**T6**) and identifying unique collectibles among all exhibits (**T4**).

Description: The *Scarcity Analysis View* (Fig. 4 B) comprises two vertically aligned regions: the upper region displays glyphs of NFT collectibles, while the lower region presents a heat map calendar that highlights the frequency and timestamps of transactions. The exhibition region is organized in the form of an ordered array of glyphs based on the chronological sequencing of transactions. Each glyph consists of three distinct parts (Fig. 4 C). The outer donut is symmetrically divided, with the left-hand arc signifying the normalized transaction price (green), while the right-hand arc represents the scarcity score (violet) as determined by equation (4). The original NFT collectible images are shown in the foreground to aid user comprehension. Users can access information such as its name, precise price, scarcity score, and transaction timestamp by hovering over a glyph of interest.

The lower heat map calendar records the daily transaction timestamps and frequencies. Data is represented through a cell-based system whereby each cell signifies a day. These cells are organized into columns representing weeks that are grouped by months. Cell opacity indicates the number of successfully traded NFT collectibles on a given day. Users can select a cell to view corresponding highlighted glyphs for detailed information.

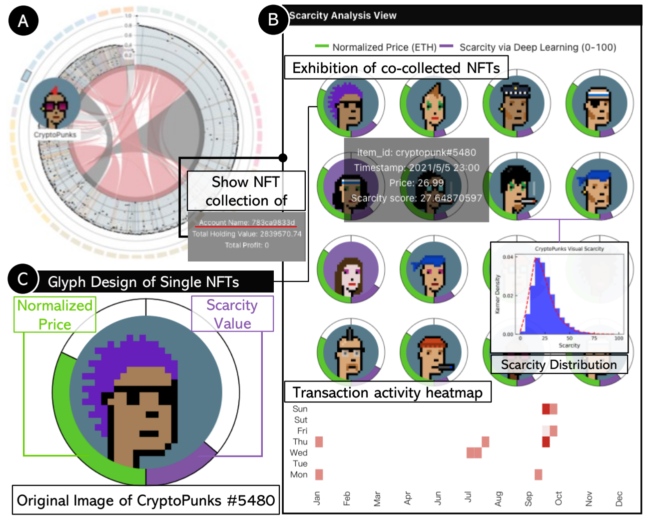

Figure 4: (A) Co-occurring whale accounts of CryptoPunks and in-between trading flows; (B) Co-collected NFTs of one whale account; (C) The glyph design of single NFTs.

Justification: We considered using a highly-summarized matrix graph to illustrate the overview of all NFT collectibles. Nevertheless, our domain experts advised against this approach, suggesting that it may be too sparse and confusing for the target users.

6 EVALUATION

This section introduces case studies with three domain experts, i.e., E_A, E_F, and E_G (see Appendix I), and their subsequent feedback.

6.1 Case Studies

6.1.1 Study 1: Prospective NFT Collection Projects. E_F expects to develop strategic action rules for identifying potential NFT collection projects based on the historical trends observed in the market's evolution (**T4, T5**). He emphasized that failing to adopt informed action plans could lead to significant financial losses due to the rising exchange rates of cryptocurrencies and high service fees associated with NFT investments.

E_F started from the *Market Share View* to browse potential prospective projects which were not dominant in the marketplaces and narrowed it down to around 40 projects by filtering the *Project Ranking View* with the latest floor price. Then E_F picked out three candidates with growing price trends but relatively low market shares: NFTrees, Veefriends, and Doodles. Afterward, E_F separately explored the three candidates' transaction frequencies and co-occurring whale accounts through the augmented chord diagram (Fig. 5). He found that Veefriends got the most co-occurring whale accounts with the highest transaction frequency, NFTrees was distantly behind, and Doodles involved the least whale accounts with the lowest transaction frequency. Accordingly, E_F identified Veefriends as one of the better prospective projects.

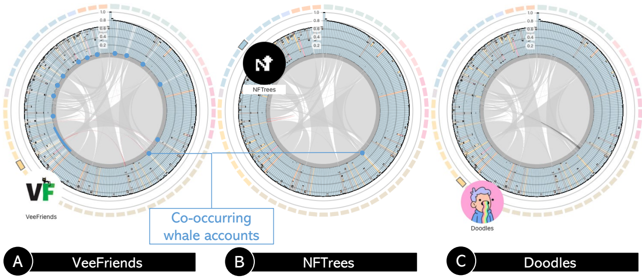

Figure 5: Case study 1: Co-occurring whale accounts of Veefriends (A), NFTrees (B), and Doodles (C).

6.1.2 Study 2: Luxury vs. Fast-Moving NFT. The differentiation of NFT collectibles into either "luxury" or "fast-moving" categories is a complex issue that can pose challenges for collectors (**T3, T6**). E_G explored this goal utilizing *NFTeller*.

E_G initiated the analysis with the *Whale Account Co-collection View* to examine the commonly co-collected NFT collection projects. The results revealed that CryptoPunks appeared most frequently among these projects, regardless of the number of whale accounts presented (refer to Fig. 4 A). This trend indicated that CryptoPunks enjoyed higher reliability than others. To test this hypothesis, E_G delved deeper into the *Attribute Analysis View* of CryptoPunks. Interestingly, she discovered that, unlike other NFT collection projects, the sales volumes of CryptoPunks remained relatively unaffected by social media communication effects. Accordingly, E_G concluded that CryptoPunks belonged to the exclusive "luxuries" category, as they were immune to short-term social media promotions.

E_G also explored another potential NFT collection project that could be considered "luxury" - Bored Ape Yacht Club (BAYC). She started from the *Project Ranking View* and noticed that BAYC had the lowest ranking based on its latest floor price, regardless of its significant market share. This observation indicated that despite having dominant sales volumes, the project might benefit more from a quick turnover than a brand premium. To validate this observation, E_G investigated the *Whale Account Co-collection View* and discovered that BAYC was barely highlighted. Consequently, E_G summarized that the target consumers of BAYC were mainly the general public other than whale accounts, and at that time, BAYC was inferior to those "luxuries" projects.

6.1.3 Study 3: Opportune Moment for Investment. E_A regarded the trend of popularity and sentiment polarity on social media as the forecast of NFT marketplaces' volatility in the near future (**T1, T2**). Thus, he tried utilizing the *Attribute Analysis View* to determine the optimal timing for investment.

E_A started from the *Project Ranking View* to inspect the floor price trends of all NFT collection projects. He found that current NFT marketplaces and NFT stakeholders tended to favor newly launched NFT collection projects, which caused similar price peaks closely following the release date. Then, E_A explored the *Attribute Analysis View* to obtain more details concerning sales volume trends, social media communication effects, and whale accounts behaviors. Moreover, E_A noticed that the market share of NFT collection projects that only had one peak would gradually decrease and attract very limited whale accounts. In contrast, projects whose attribute evolution illustrated regular fluctuations had a longer market life cycle

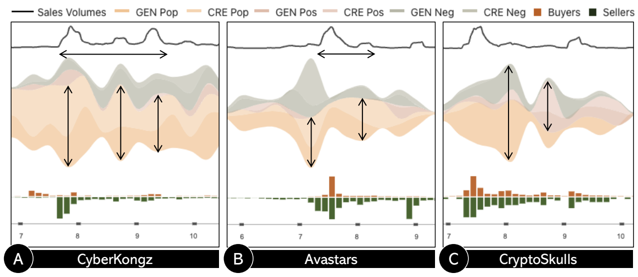

Figure 6: Case study 3: The market performances of CyberKongz (A) and Avastars (B) are parallel with social media communication effects. The market performance of CryptoSkulls (C) soared with influencers' endorsements.

(Fig. 6 AB). When NFT influencers recommend certain projects on social media could also cause a stable increase afterward (Fig. 6 C). E_A further drilled down to Spearman's rank correlation coefficient graph and found that social media popularity positively correlated with sales volumes and floor price. Thus, he concluded that it would be better to "procrastinate" a little bit and wait for the next climax on social media as the indicator of investment.

6.2 Expert Interview

We conducted semi-structured interviews after case studies to gain feedback and advice from domain experts (see Appendix IV).

Procedure. Every interview encompassed three sessions and lasted over 60 minutes. First, we introduced the dual-centric workflow of our system using CryptoPunks as an instance (20 mins). Second, we invited domain experts to fulfill three tasks by think-aloud protocol (20 mins): (1) select one popular NFT collection project; (2) detect significant impact attributes; and (3) derive insights for assessing NFTs. Finally, we summarized their comments and advice on *NFTeller* for further optimization as follows (20 mins):

System Usability. Overall, three domain experts completed the three tasks within the allotted time and commented that *NFTeller* was useful (see quotes in Appendix V.1). Specifically, they identified the *Project Ranking View* and the *Whale Account Co-collection View* as particularly useful for identifying popular NFT collection projects, while the *Attribute Analysis View* was most relevant for detecting impact factors. In addition, they found that the *Scarcity Analysis View* was essential for locating unique NFT collectibles. However, they recommended incorporating real-time data into *NFTeller* (E_A) and implementing a noticeable reminder mechanism when whale account transactions happened (E_F).

System Effectiveness. Our domain experts acknowledged that *NFTeller* was effective compared with their previous workflows (see quotes in Appendix V.2). However, they also suggested using more zoom-in techniques for the *Attribute Analysis View* and *Whale Account Co-collection View* to increase clarity and precision in analysis. The domain experts noted that, on occasion, these two views were "*too abstract to derive insights at short notice*" (E_G).

Visual Designs and Interactions. Three domain experts generally regarded this system as understandable and intuitive (see quotes in Appendix V.3). In particular, the *Whale Account Co-collection View* and *Scarcity Analysis View* were often mentioned as being informative and interesting. E_F reported that combining these two views could provide a quick index for him to discover the specific NFT collection projects he would explore further. Nevertheless, they also suggested displaying more fine-grained information, such as "*present some keywords from original tweets*" (E_F) and "*separately illustrate the sell and buy actions of every single whale account*" (E_A).

7 DISCUSSION

Limitations. The limitations of *NFTeller* are threefold. First, **scalability**. The system illustrates transaction data of 61 NFT collection projects and collection records of 600 whale accounts in 2021. Although with filter and navigation interactions, the exploration process still piles up users' memory burden. Some potential improvements could be conducted, e.g., aggregating impact attributes to cluster NFT collection projects and generating an overview of the marketplaces. In addition, a highly summarized image browser based on mutual similarities could be adopted to depict the scarcity patterns of NFT collectibles. Second, **impartiality**. The system detects one *static* and two *dynamic* impact attributes for evaluating NFT collectibles derived from semi-structured interviews. Although our collaborators are experienced domain experts, their insights could be partially subjective. Third, **data issue**. *NFTeller* only considers NFT transaction data on Ethereum in 2021. Although the data sampling is limited, we believe the NFT collection projects analyzed in our system are representative for two reasons. Firstly, NFT-tied assets are diversified in categories and characteristics, which implies mixing all categories could be problematic. Secondly, 2021 is the most prosperous year of NFT marketplaces, with NFT collectibles taking the biggest market share, which suggests our sampling could generally reflect the evolution of the whole market.

Generalization. Apart from NFT collectibles, *NFTeller* can be extended to other domains. Firstly, other NFT-tied assets with visual features, such as NFT fine art and NFT game properties, could be analyzed by our system. Secondly, our system's visual design and workflows could apply to other creative industries with heterogeneous multi-modal data (e.g., traditional art markets and movie industries). Besides, the augmented chord diagram with a radial stacked bar chart could visualize other bipartite set relations. For instance, it can exhibit the cooperation between scholars from different paradigms to detect the interdisciplinary research trend.

8 CONCLUSION

In this work, we proposed a visual analytics system, *NFTeller*, for NFT assessment with a dual-centric workflow and intuitive visual designs. In collaboration with domain experts, we characterized one *static* and two *dynamic* impact attributes and identified three categories of tasks. Accordingly, we developed *NFTeller* with five well-coordinated views and flexible interactions. Further, we validated the effectiveness and usability of our system via three insightful case studies and semi-structured interviews with domain experts. The results demonstrated that *NFTeller* could efficiently assist users in assessing the market performance of NFT collectibles.

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