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Hedonic and Utilitarian Valuation Determinants of NFT Collections in the Post-Bubble Market

Pragya Singhal
pragya090409@gmail.com

ABSTRACT

Since their inception in 2017, non-fungible tokens (NFTs) have evolved into a distinct digital asset class characterized by cryptographically verifiable ownership and multifaceted valuation logics. Prior scholars have established a robust foundation for understanding NFT valuation by identifying key hedonic and utilitarian drivers within NFT collections. However, a research gap remains regarding the joint impact of these determinants across a broader cross-collection scope within the post-2021 crypto bubble landscape.

This study's objective was to statistically examine how measurable hedonic and utilitarian traits influence collection-level NFT valuation after the 2021 hype market, and which determinant exerts the highest positive impact on valuation. To investigate this relationship, a multivariate cross-sectional quantitative causal-comparative analysis was conducted. Using a log-linear hedonic regression, eight measurable traits were examined in relation to the floor price of 46 collectible (PFP) NFT collections selected from OpenSea.

It was found that not all traits positively influence NFT valuation as previously assumed. Additionally, it was concluded that the hedonic trait of 'External Validation' exerts the highest positive impact on valuation and is the most statistically significant, indicating that in the post-bubble market, credibility and third-party assurance (through brand partnerships and celebrity endorsements) appeal to cautious NFT investors. These results elucidate the shifting pricing dynamics within the NFT market ecosystem, and provide a strategic framework for creators, brands, investors, and regulators to strengthen current valuation frameworks.

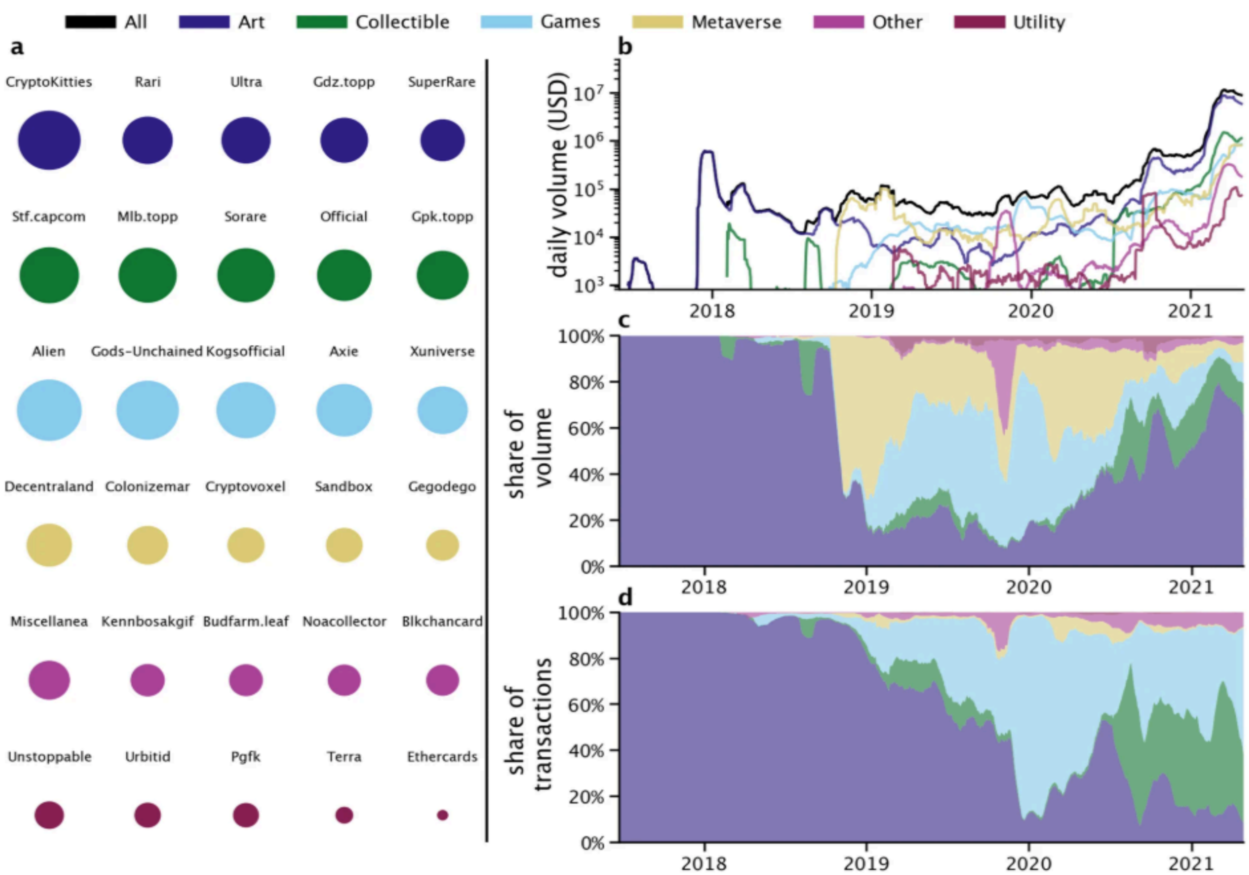
KEYWORDS: Non-Fungible Tokens (NFTs), Asset Pricing, Post-Bubble, Signaling Theory

INTRODUCTION

The mainstream emergence of non-fungible tokens (NFTs) after 2017 established a novel class of digital assets with cryptographically verifiable scarce ownership rights, minted and traded on the Ethereum blockchain (see Appendix A). NFTs surged in popularity during the COVID-19 pandemic and the trading volume experienced a 115% growth by late 2020 (Perez et al., 2023). In fact, "NFT" was crowned Collins Dictionary's word of the year for 2021, and in the same year, sales grew by more than 61,000% (Mekacher et al., 2022). According to Stanford Visiting Fellow Kräussl and doctoral researcher Tugnetti, the industry's publicized peak allowed transactional revenue to escalate exponentially from $1.5 billion in January 2019 to $180.8 billion in December 2022, giving rise to a heterogeneous, active secondary market (Appendix A) shaped by emotional and functional pricing logics concerning NFTs (Kräussl & Tugnetti, 2023).

Within this rapidly expanding ecosystem, assets are organized into collections, sets of NFTs sharing common features. These are owned by various players — major corporations, decentralized groups, private collectors, artists, and even celebrities. As visible in Figure 1, NFT collections are functionally

Figure 1: *Distribution of Top NFT Collections by Category and Volume*



Note. Panels summarizing the NFT landscape. (a) Top 5 NFT collections organized by category, with circle size proportional to the number of assets. (b) Daily volume (USD) exchanged over time for each category and all assets, with days under 1000 USD volume excluded. (c) Share of volume traded by category. (d) Share of transactions by category. Results are averaged over a rolling 30-day window. Reprinted from *"Mapping the NFT revolution: market trends, trade networks, and visual features"* by Nadini, M., Alessandretti, L., Di Giacinto, F., Martino, M., Aiello, L. M., & Baronchelli, A., 2021, *Scientific Reports*, *11*(1), 20902 (https://doi.org/10.1038/s41598-021-00053-8). Copyright 2021 by Nadini, M., Alessandretti, L., Di Giacinto, F., Martino, M., Aiello, L. M., & Baronchelli, A. Licensed under CC BY 4.0 (http://creativecommons.org/licenses/by/4.0/).

diverse, ranging from collectible cards to virtual spaces in online gaming, but fall into six main categories: Art, Collectible, Games, Metaverse, Other, and Utility (Nadini et al., 2021). Prominent examples include CryptoPunks, CryptoKitties, Bored Ape Yacht Club (BAYC), Decentraland, among others, each comprising thousands of unique tokens.

Similar to art objects serving a dual purpose of aesthetic pleasure and financial value (Cifuentes & Charlin, 2023), NFTs exhibit several features, and their valuation is dependent on both emotional appeal-driven hedonic traits and perceived usability-fueled utilitarian traits (Appendix A). Surveying an NFT-interested targeted group recruited via Facebook, Discord, Messenger, and Reddit, Fortagne & Lis (2023) found that mechanistic attributes (functionality, price value, security, and privacy) link to utilitarian consumer attitudes, while design-oriented traits (scarcity and aesthetics) drive hedonic behavior. Mediation analysis further revealed that product and blockchain technology features indirectly influence purchase intention, signaling that NFT demand emerges from a blend of practical assurances and experiential appeal.

Despite these emerging insights, prior research primarily explores hedonic and utilitarian price determinants in isolation, and largely focuses on individual NFT collections. This study seeks to bridge this divide by examining the combined effect of hedonic and utilitarian traits on collection-level valuation within post-2021 hype phase market dynamics. The findings derived can inform investors, creators, marketplaces, policymakers, and researchers by advancing valuation frameworks in an evolving digital asset ecosystem.

Literature Review

Search Strategies

Sources were identified across peer-reviewed databases by employing key search strings that coupled NFT terminology with valuation-focused descriptors through Boolean operators (e.g., AND, OR).

Theoretical Foundations and Cross-Market Insights from Art Investments

Long-established traditional art markets offer a valuable interdisciplinary lens uniting finance, behavioral economics, and investor psychology to understand the pricing of aesthetic commodities, many of which share characteristics with NFTs.

One of the earliest examinations of art as an investment by economist William Baumol, professor emeritus at Princeton University, characterized the market as speculative, noting that average real returns on art are close to zero and often fall below established financial assets (Baumol, 1986). Analyzing centuries of auction data, the research described price movements as a “floating crap game” where past market information provides limited predictive value, emphasizing the anchorless nature of art valuation. However, seasoned art economists Buelens & Ginsburgh (1993) revisited Baumol’s “pessimistic” conclusion in the *European Economic Review*. By reconstructing his sales database and subdividing by strata, they found that specific art market segments yielded returns exceeding bonds and stocks over 20-40 year periods. Their analysis signaled greater variability in behavior across genres and periods, depicting a mix of under-performing and high-performing categories. This suggests the art market is heterogeneous (Appendix A) rather than uniformly speculative, a characteristic directly mirroring the diverse NFT ecosystem.

Subsequent researchers have built upon the debate behind art's psychological and financial returns by introducing varied statistical tools to measure how specific traits influence price. Authors at the University of Delaware applied log-linear hedonic price regressions to auction data of American paintings sold between 1971 and 1992, reporting average nominal returns above 9% and real returns around 3% (Agnello & Pierce, 1996). Mirroring Buelens and Ginsburgh (1993), they stratified selections using quantifiable attributes including size, authenticity, artist reputation, auction house etc., concluding that return rates are highly sensitive to systematic data categorization and art investments align closely with traditional investments. Yet, economists at the University of Zurich critique the methodological frameworks, data sources, and measurement gaps of such empirical studies estimating art returns, noting that most report lower appreciation than financial assets (Frey & Eichenberger, 1995). They identify common limitations in literature like reliance on auction data, omission of transaction costs/taxation, and mechanistic calculations that ignore institutional and behavioral market features, calling for richer evaluation methods accounting for "psychic returns" or the non-financial pleasure derived from art ownership. Addressing this need, Sukhani (2025) offered a comparative analysis of behavioral biases between diverse investments, finding that endowment bias (Appendix A) is significantly stronger in art than in stock markets. This heightened attachment to art holdings explains that investors derive unique satisfaction from such assets beyond purely financial considerations.

Complementing these internal psychological attachments, studies highlight that external validation acts as a strong factor influencing the valuation of traditional art assets. According to authors at the Renmin University of China, Erasmus University, and Tilburg University, trust is essential in markets, but particularly more for "illiquid, opaque, and largely unregulated markets, such as the art market" (Li et al., 2022). Using textual analysis and hedonic regression, their study found how provenance (measured by pedigree, exhibition history, literature coverage, and certification) can guarantee authenticity and emit trust signals in the information asymmetrical art market, generating hammer price premiums of up to 54%. It also revealed that pedigree, or ownership history, is particularly influential; the presence of high-status individuals, such as celebrities, CEOs, or historic families, within a chain of custody serves a tripartite function: it signals that previous owners could afford trust, suggests the work was curated to meet elite standards (quality), and provides a "glamour premium" for buyers who desire a physical association with admired figures. Similarly, broader literature explores the concept of "contagion," where consumers believe an object retains some essence of its former owner, and physical association with high-profile individuals like celebrities significantly increases their willingness to pay (Newman et al., 2011). Furthermore, institutional validation acts as a proxy for artistic quality. As noted in the *European Societies* journal published by the MIT Press, the value of an artwork arises from an intersubjective process of assessment by experts in the art field, including curators, gallery owners, critics, art dealers, journalists, and collectors (Beckert & Rössel, 2013). The statistical analysis of auction price data also revealed that the most meaningful reputation indicator is media awareness and recognition of artists, which lends legitimacy to their artwork. Ultimately, these signals of expert authentication, media awareness, and celebrity ownership history legitimize art assets as authentic financial commodities, directly expanding the baseline willingness-to-pay among collectors. Therefore, given the structural parallels in information asymmetry and subjective value, it can be valuable to look at the NFT market through these similar signals of external validation which may reduce buyer uncertainty.

Nevertheless, there is little doubt that this subjectivity and opaque nature of the art market causes it to be highly volatile as stated by Baumol (1986). Burton & Jacobsen (1999) performed a meta-analysis of methodologies concerning the returns of collectibles like art, coins, and stamps, finding that while most collectibles provide positive real returns, they carry higher idiosyncratic volatility (Appendix A) and typically underperform stocks. They emphasized that returns on collectibles are negatively correlated with bull markets (Appendix A) and warned of boom-bust dynamics and limited hedging benefits (Appendix A), underscoring the importance of risk-adjusted measurement when assessing these investments. Extending and refining their perspective, a study by the Sotheby's Institute of Art, which specializes in art business education, examined art investment funds case studies to evaluate their risks, long-term returns, and transaction costs. It concluded that while unsuitable as standalone investment options, these can enhance portfolios and offer resilience against economic downturns (Chen, 2025). Thus, art can serve as a strategic, albeit limited, component of a diversified (Appendix A) investment strategy.

Together, these studies spotlight how intersubjective art markets blend aesthetic attributes, economic fundamentals, and institutional trust signals in determining value. Ergo, NFT valuation can be better understood when viewed through the same established framework.

Hedonic Traits Influencing NFT Pricing

Researchers have identified common threads between hedonic characteristics driving NFT prices using diverse methods.

One fundamental hedonic component influencing NFT valuation is attribute rarity. A study published by *The Journal of The British Blockchain Association* analyzed CryptoPunks' attributes such as type, hair color, facial features, and accessories, observing that rarer traits like the "Alien" type, in Figure 2 (as seen in token IDs 2890, 7804, 635), raise prices (Schaar & Kampakis, 2022). This suggests that scarcity tends to attract heightened consumer demand and speculative interest since it signals a sense of exclusivity, and thus greater value. These findings are supported by authors at the University of London and Visual Artificial Intelligence Lab at IBM Research, who examined heterogeneous rarity patterns across 1.4 million NFTs using a set of human-readable attributes (Mekacher et al., 2022). Their results also reveal that on average, rarer NFTs (i) sell for higher prices, (ii) are traded less frequently, (iii) yield higher returns on investment, and (iv) exhibit lower risk. Likewise, Lee et al. (2024) examined the BAYC NFT collection through a rigorous Formal Concept Analysis method, demonstrating that rarity profoundly governs prices, particularly in the medium scarcity range. Thus, findings across NFT literature align: rarity increases valuation and investment stability (Appendix A).

Figure 2: *Sample of Top CryptoPunks Highlighting Rare "Alien" Trait and Other Attributes*

Note. Pictures depicting a sample of eight of the 20 most valuable CryptoPunks. The numerical values represent the NFT IDs of the respective tokens in the CryptoPunks collection. The "Male" type (in token IDs 344, 2204, 3307, 7846, 89) is common, while the green-skinned "Alien" type (in token IDs 2890, 7804, 635) is a rare trait. Reprinted from *"*Non-fungible tokens as an alternative investment: Evidence from CryptoPunks*"* by Schaar, L., & Kampakis, S., 2022, *Journal of the British Blockchain Association*, 5(1), 2, (https://doi.org/10.31585/jbba-5-1-(2)2022). Copyright 2022 by Schaar, L., & Kampakis, S. Licensed under CC BY 4.0 (http://creativecommons.org/licenses/by/4.0/).

Beyond scarcity, aesthetics and visual features play a consistent role in NFT price formation. Evidence from empirical work on the CryptoPunks collection by Associate Professors in Finance, demonstrated that measurable hedonic visual traits including colorfulness, brightness, saturation, and texture complexity, command NFT prices (Alsultan & Markellos, 2024). These insights suggest that attribute-specific visual features and pattern intricacy guide market differentiation and valuation. Corresponding to these results, Kaur & Renneboog (2024) analyzed pixel intensity across the 24×24 RGB (red-green-blue) color matrix for 14,000+ CryptoPunks and calculated visual rarity scores, identifying that aesthetic uniqueness matters most for mid-tier NFTs. This is because buyers in this range have greater sensitivity to subtle visual distinctions, signaling that stylistic differences drive demand in NFT markets. Identically, Wu et al. (2023) applied multiple mixed-method approaches and found that NFT collectibles and creative artworks exhibiting design features like "cute," "beautiful," and "interesting" are the most attractive and dominate markets. Hence, visually pleasing appearance and unique artistic design harmonize, appealing to consumer preferences and elevating NFT prices.

Additionally, several studies have placed emotional value, personal enjoyment, and social engagement at the forefront of NFT buyer interest. Authors affiliated with the ISEG Lisbon School of Economics & Management surveyed 482 NFT buyers using the SIMS (Situational Intrinsic and Extrinsic Motivation Scale) framework, discovering that intrinsic motivations (Appendix A) such as enjoyment and personal satisfaction strongly predict NFT purchase intent, while extrinsic motivations (Appendix A) like social or monetary gains are weaker impetus (Griffiths et al., 2024). Moreover, they characterize NFT collectors as similar to luxury-goods consumers making purchase choices based on emotional resonance over social comparison, incentives, or herd behavior. This reveals that NFT valuation is largely driven by individual preferences rather than conventional market forces. In direct contrast, a study published by the Oxford University Press, analyzed marketplace data for 1,104 OpenSea collections, concluding that social value (Appendix A), community building, and popularity can outweigh intrinsic asset value (Appendix A) as a determinant of willingness-to-pay, and even reverse the typical positive effect of NFT scarcity on price (Hofstetter et al., 2024). This implies NFT pricing is not completely independent of broader market behavior as social buzz signals and user engagement amplify demand beyond inherent asset worth and crypto fundamentals. Elaborating on the social value factor established by Hofstetter and co-authors, An & Chang (2024) offered new insights. Using quantitative data from the Bored Ape and Mutant Ape collections on NFT marketplaces like OpenSea, SuperRare, and Nifty Gateway, they ascertain that NFTs listed on more popular platforms like OpenSea command greater demand and sell for higher prices. Therefore, platform-level effects and social visibility contribute to market dynamics and valuation for NFT collections and assets, along with emotional appeal and community hype.

Synthesizing the literature, it becomes clear that NFT pricing hinges on a dynamic interplay between hedonic characteristics like rarity, aesthetics, sentiments, social signaling, and platform effects, which collectively produce rapid price spikes.

Utilitarian Traits Influencing NFT Pricing

While most studies focus on hedonic traits, some scholars also acknowledge utilitarian elements behind NFT valuation and buyer interests. In fact, Zalan & Toufaily (2024) interviewed 38 NFT collectors, finding the consumer value behind NFTs is primarily utilitarian.

Research highlights that NFTs with real-world buyer benefits can function as practical marketing instruments for reinforcing social visibility and community engagement. Quantitative modeler Colicev highlights NFTs' potential to become standalone brand assets and community building tools in Figure 3 continued (Colicev, 2022). He cites examples of fashion brands like Nike and Adidas that tokenized their physical footwear into NFTs to enhance product awareness, drive cross-selling, and foster perceived ownership. This suggests that merchandise-linked utility is associated with sustained buyer demand which may shape NFT valuation. Furthermore, he explains how NFTs offering access-based and service-based utilities like exclusive rewards, premium services (e.g., priority concert seating), and private events (e.g., BAYC parties), can cultivate highly involved communities, thereby creating active Discord servers and strengthening omnichannel consumer-brand bonds. Clearly, these benefits increase perceived value which may encourage higher NFT sales as buyers seek to access utilitarian privileges. Colicev's comprehensive literature review is grounded by the exploratory study conducted by researchers at the Adelaide Business School, detailing the five primary NFT-based brand experiences (community, products, collaborations, gamification, brand heritage) which can enhance brand presentation and meaning (Li et al., 2025). It concludes that regardless of the functional NFT experience a brand adopts, its activities can differentiate it from other similar competitors in the blockchain, emphasizing that functional NFTs can potentially lend a comparative advantage. Expanding upon this, Brandes & Dölp (2025) further break down the forms that embedded NFT utility comes in. These include: offline/online exclusive experiences (e.g., Coachella's "Coachella Keys" NFT collection providing owners lifetime all-access festival passes), digital or physical items (eg., Lamborghini's "The Ultimate" NFT collection including physical car ownership), and unlockable content (eg., Liverpool F.C.'s NFTs granting access to the members-only LFC Heroes Club Discord community chat channel for virtual hang-outs, competitions, guest appearances, and updates). The researchers also hypothesized that since inclusion of added utility increases the value of owning the NFT, any utility has a positive correlation with revenues. In summary, distinct utilitarian traits including access to exclusive merchandise, premium content, and concierge services (Appendix A), contribute to NFT sales performance and valuation.

Figure 3: *Integrating NFT-Driven Brand and Community Strategies into the Consumer Marketing Funnel*

Note. Pyramid outlining the functional applications of NFTs in enhancing brand exposure and fostering communities across the pre-purchase, purchase, and post-purchase progression stages of the consumer marketing funnel. Reprinted from *"*How can non-fungible tokens bring value to brands*"* by Colicev, A., 2022, *International Journal of Research in Marketing*, *40*(1) (https://doi.org/10.1016/j.ijresmar.2022.07.003). Copyright 2022 by Colicev, A. Licensed under CC BY 4.0 (http://creativecommons.org/licenses/by/4.0/).

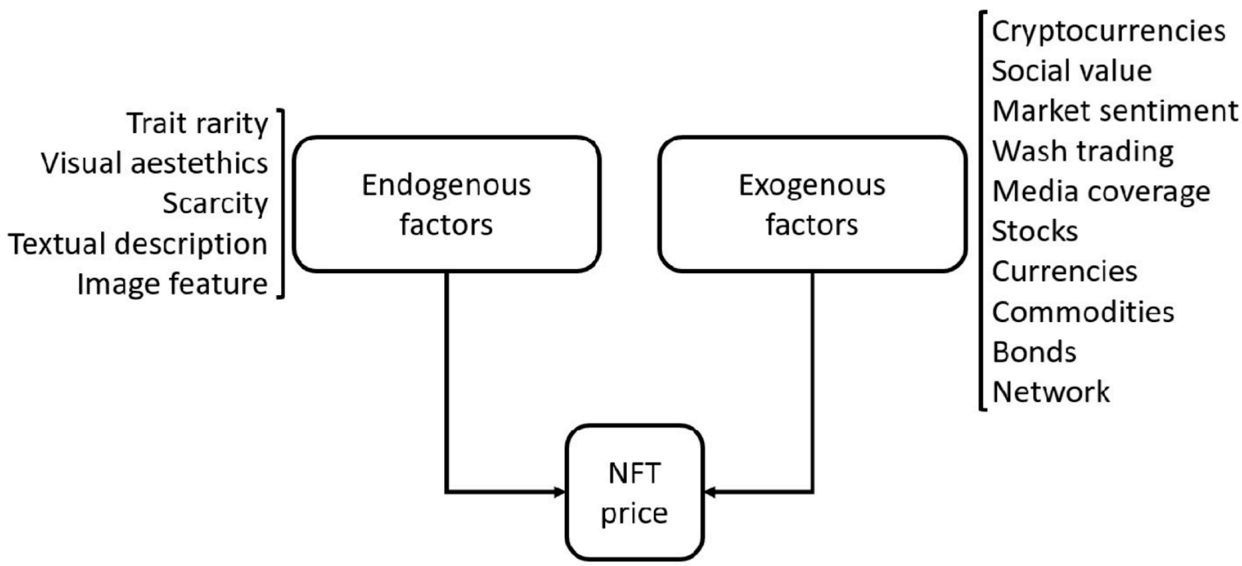
Besides branding, NFTs are also a prominent component in virtual gaming, where they function as playable or customizable assets integrated into play-to-earn models, allowing players to enjoy while simultaneously increasing their financial gains. For example, Louis, a game by Louis Vuitton, lets players complete challenges to earn customizable NFTs featuring brand patterns and colors which can be used as personal avatars in the metaverse, as stated by Voguemagazine (Li et al., 2025). Such opportunities illustrate that game-integrated utility appeals to players, promoting greater NFT demand.

Collectively, functional integration through merchandise linkage, access privileges, service entitlements, or in-game usability can attract buyer attention and create demand, driving higher sales, valuation, and potentially minimizing idiosyncratic risk in the NFT market.

Other Traits Influencing NFT Pricing

In addition to hedonic and utilitarian traits, prior research identifies other market-based elements shaping NFT valuation. Flamini & Naldi (2025) summarize some of these in Figure 4.

Figure 4: *Endogenous and Exogenous Determinants of NFT Valuation*



Note. Basic flowchart condensing endogenous and exogenous drivers of NFT pricing. Endogenous factors refer to intrinsic NFT characteristics while exogenous factors arise from external market conditions. Reprinted from *"What Is the Right Price for Non-Fungible Tokens (NFTs)? A Systematic Review of the Current Literature"* by Flaminir, M., & Naldi, M., 2025, *FinTech*, 4(4), 73 (https://doi.org/10.3390/fintech4040073). Copyright 2025 by Flaminir, M., & Naldi, M. Licensed under CC BY 4.0 (http://creativecommons.org/licenses/by/4.0/).

Research Gap and Significance

Scholarly research indicates that NFT valuation emerges from the interaction of aesthetic, emotional, social, functional, and practical considerations, underscoring the importance of integrating both hedonic and utilitarian perspectives when analyzing market behavior. Building on this understanding, this study addresses three primary gaps in existing literature.

First, current work emphasizes hedonic drivers and utilitarian traits separately, while their combined influence is tangentially addressed (Alsultan & Markellos, 2024; Fortagne & Lis, 2023; Kaur & Renneboog, 2024; Schaar & Kampakis, 2022; Wu et al., 2023). By operationalizing underdeveloped utilitarian aspects alongside established hedonic traits, this inquiry serves as an initial empirical exploration of their joint role in shaping NFT valuation, fulfilling the integration gap.

Second, much of the NFT literature relies on case studies that focus on within-collection attributes like rarity and aesthetics, largely overlooking cross-collection features (Alsultan & Markellos, 2024; Kaur & Renneboog, 2024; Lee et al., 2024; Schaar & Kampakis, 2022). This study addresses the macro gap by investigating collection-level valuation determinants including social visibility, community engagement, external validation, access to game assets, merchandise integration, and exclusive utility-driven services.

Third, most scholars focus on pioneer NFT collections such as CryptoPunks, CryptoKitties, and Decentraland, which were launched before the pandemic and peaked during the 2021 boom phase (Alsultan & Markellos, 2024; Kräussl & Tugnetti, 2023). Minimal research examines collections which emerged during or after this broader speculative crypto bubble (Appendix A) and sustained market presence. To address this temporal gap, the present research focuses exclusively on collections launched during or post 2021.

Amalgamating these underexamined dimensions motivates a closer investigation into the factors impacting NFT valuation. Subsequently, observing multifaceted NFT characteristics is crucial for evaluating their role across various evolving sectors and alignment with distinct consumer group expectations (Li et al., 2025). Moreover, the high-impact journal *Finance Research Letters* notes that despite their short history, NFTs appear to be establishing themselves as valuable alternative financial assets within the blockchain ecosystem instead of merely being derivatives of cryptocurrencies (Horky & Hohenberg, 2022). This renders research concerning their market dynamics all the more important. Accordingly, this study asks: How do hedonic and utilitarian characteristics across NFT collections influence collection-level valuation post the 2021 hype market, and which determinant exerts the highest positive impact on valuation?

Hypotheses

H_1 : All hedonic signaling (community engagement, social visibility, external validation) and functional utility (access to game assets, merchandise integration, exclusive experiences/features) traits will demonstrate a statistically significant positive relationship with the valuation of NFT collections in the post-hype market.

The rationale for H_1 is grounded in Consumer Theory and Consumer Culture Theory (Appendix A), which posit that both functional utility and hedonic signaling contribute to an asset's consumption. In a maturing digital market, it is expected for investors to seek both rational, tangible benefits (utility) and emotional-social status (hedonic) in alignment with previous literature. This dual-intent consumption is expected to positively correlate with collection-level valuation.

H_2 : External validation will exert the highest relative influence on collection-level valuation compared to other modeled variables.

The rationale for H_2 stems from Signaling Theory (Appendix A) in environments of high information asymmetry. Because the intrinsic or fundamental value of NFT assets is often opaque, market participants might rely on external validation from established entities as a proxy for credibility. This mirrors traditional art markets, where expert authentication, media recognition, and high-status provenance dictate pricing over physical asset traits by directly reducing buyer uncertainty. Resolving this trust deficit is the primary barrier to transaction in opaque markets, and hence, external validation is expected to outweigh other metrics in its influence on valuation.

METHOD

Overview

This multivariate cross-sectional retrospective study employed a quantitative causal-comparative analysis (Appendix A) across multiple NFT collections to statistically examine how measurable hedonic and utilitarian features relate to collection-level valuation. The cross-sectional design (Appendix A) was essential to capture data under identical market conditions in a fixed timeframe. The causal-comparative analysis allowed comparisons across collections to identify possible cause-and-effect relationships without experimentally manipulating the data.

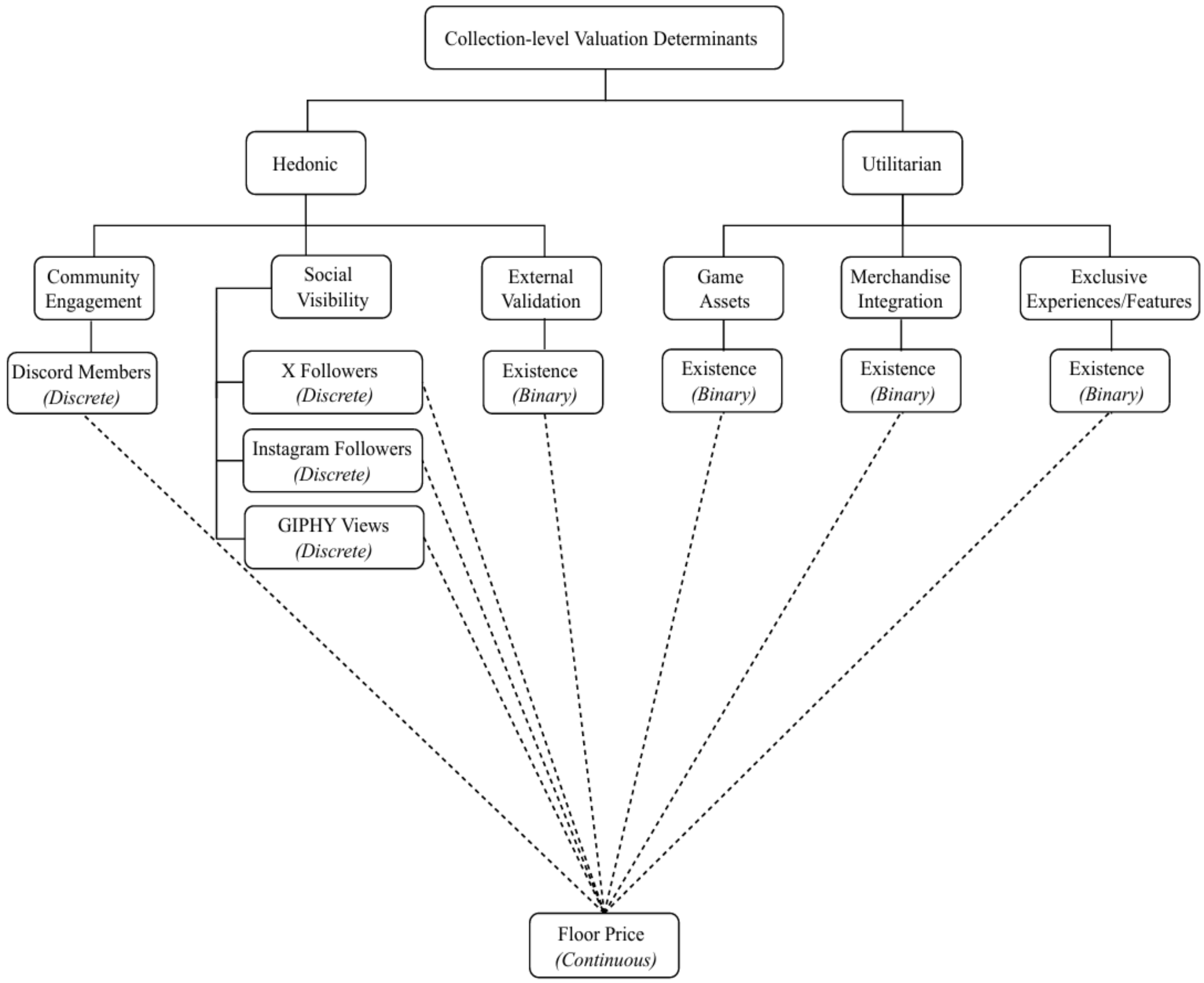
Research Design

Variable Operationalization

A dual-framework approach was used for categorizing research variables into distinct hedonic and utilitarian branches to analyze their effect on NFT valuation, as seen in Figure 5.

Hedonic determinants were operationalized through community engagement, social visibility, and external validation. Community engagement was measured through the number of Discord members, a discrete (counting) variable, as done by Zhang et al. (2025) who found that the "fan economy" on Discord positively affects NFT pricing. Measurement of social visibility was triangulated through cross-platform metrics including the number of X followers, Instagram followers, and GIPHY views, which were also grouped as discrete variables. Since platforms like X and Instagram allow original creators to promote their NFTs and buyers to resell them, features such as the number of followers, shares, likes, views, and other interactions on these have extensively been used in NFT literature to identify broad market reach, popularity, and purchase intention (Boeck et al., 2025; Brdesee & Alsaggaf, 2021; Kapoor et al., 2022; Muñoz et al., 2022; Trunfio & Rossi, 2021; Vasan et al., 2022; Zhang et al., 2023; Zhang et al., 2025). However, this study only focused on the number of followers on these two platforms for feasibility following Ziemke et al. (2023), along with the number of GIF views on GIPHY, the leading GIF platform

Figure 5: *Structural Model of Hedonic and Utilitarian Influences on Floor Price*



Note. Flowchart illustrating the multivariate relationship between the independent variables (collection-level hedonic and utilitarian factors) and the continuous dependent variable (floor price). Hedonic factors including community engagement, social visibility, and external validation; and utilitarian factors including access to game assets, merchandise integration, and exclusive experiences/features are operationalized through discrete (counting) and binary (0/1) variables. Specifically, for each selected NFT collection, discrete variables quantify community engagement (through number of Discord members) and social visibility (through number of X followers, Instagram followers, and GIPHY views), while binary variables quantify the presence/absence of external validation, game assets, merchandise integration, and exclusive experiences/features.

(GIPHY, 2019). While GIFs have not been previously studied in the context of NFTs, scholars agree they are visually communicative, highly engaging, emotion-generating tools which can translate into virality on digital social and community networks (Bakhshi et al., 2016; Jiang et al., 2018; Miltner & Highfield, 2017; Rúa-Hidalgo et al., 2021). Thus, GIPHY views were also used to gauge social visibility. Finally, the existence of external validation was measured as a binary variable (1 = presence & 0 = absence) to indicate a collection's mainstream legitimacy, mirroring previous researchers' approach to model dichotomous traits which only have two possibilities (Brandes & Dölp, 2025; Li et al., 2025). More specifically, external validation was coded as 1 if the collection satisfied at least one of these threshold criteria: (i) endorsed or purchased by a public celebrity with over one million cumulative followers across X and Instagram, or a public figure ranked in the top-tier of their industry based on Fortune global indices; or (ii) officially partnered with a Fortune Global 2000 brand. The one-million-follower threshold is widely recognized as a credible metric of celebrity status (Lee et al., 2024). Additionally, although celebrities are rarely domain experts in blockchain technology, their purchase/endorsement of an NFT leverages massive social influence to grant the collection status, legitimacy, and visibility, which subsequently drives market demand (Newman et al., 2011). Similarly, Beckert & Rössel (2013) found that media recognition serves as the primary institutional validation indicator for traditional artists. Extending this framework to digital assets, it is logical that NFT partnerships with corporate brands possessing Fortune media authenticity function as trustworthy, third-party approval signals (Zhang et al., 2026). In summary, these hedonic metrics of community engagement, social visibility, and external validation were critical to quantify the social signaling power and "hype" that drive emotional value in the NFT market.

Conversely, utilitarian attributes were operationalized through access to game assets, merchandise integration, and exclusive experiences/features. These were also quantified using binary variables to indicate their presence (1) or absence (0) for each collection. While Brandes & Dölp (2025) utilized a singular, binary, aggregate utility metric, this research refined it by subdividing utility into three distinct indicators for a granular assessment of which isolated functional benefit most significantly correlates with price. Game assets referred to whether a collection offered functional, playable, or customizable digital items within a gaming or virtual ecosystem (Li et al., 2025). This was coded as a 1 if the NFT collection tokens possessed active virtual utility, for example, Azuki offering integrated trading card games and hosting national invitational gaming tournaments, or CyberKongz utilizing playable VX avatars within the Sandbox metaverse. Merchandise integration was defined as the verified existence of physical apparel, consumer goods, or commercial products structurally integrated with the collection's brand ecosystem (Colicev, 2022). This utilitarian variable was satisfied if the collection actively facilitated physical or digital product lines independently or through brand collaborations. For instance, Doodles distributes kids' apparel, puzzles, physical toy collectibles, bags, hoodies, plushies etc., and Milady Maker independently and collaboratively manufactures branded bags, shirts, stickers, and cosmetics. Finally, exclusive experiences and features captured whether a collection hosted high-utility, gated concierge perks (Brandes & Dölp, 2025; Colicev, 2022). This included whether a collection offered entry into premium real-world networking events, restricted-access gatherings, physical/digital facilities, proprietary tools, content channels, or reward systems. For example, World of Women has organized nearly 180 global events, meetups, and galas for its over 540,000 members, which include figures like Reese Witherspoon, Madonna, and Sofía Vergara. Likewise, Moonbirds implements a reward point system called 'Talons' to grant holders access to exclusive in-person and digital experiences, exhibitions, and collectible drops. These utilitarian traits of game assets, merchandise integration, and exclusive experiences/features measured the practical benefits for investors, providing the psychological anchor necessary to rationalize participation in a highly volatile market.

Other notable independent traits omitted from the model include scarcity and aesthetic appeal. While internal token scarcity (rarity) is a documented driver of pricing dynamics in NFT literature, this trait operates strictly at the within-collection level (Lee et al., 2024; Schaar & Kampakis, 2022). Every collection inherently possesses rare tokens, and evaluating scarcity requires combining the frequency rates of specific attributes/accessories to determine how unique an individual token in a collection is. Since this study employs a cross-collection analysis and scarcity is not a quantifiable collective metric for each NFT collection, it was excluded as a relevant comparative factor. Additionally, aesthetic appeal was omitted due to the inherent visual subjectivity of digital art and the lack of a standardized, quantifiable metric to evaluate artistic features across heterogeneous collections. Consequently, to maintain model objectivity and focus on measurable collective attributes, both scarcity and aesthetics were excluded due to this research's structural scope and data measurement limitations.

Ultimately, the selected independent hedonic and utilitarian variables converge to influence the valuation, measured by floor price. Floor price indicates the lowest selling price of an NFT in a collection, and sets the baseline for the collection's value by measuring the market's valuation floor (Fridgen et al., 2024; Szydło et al., 2023). Individual final auction prices were not utilized as a dependent variable because they distort aggregate data; for instance, a single highly rare NFT may command an extremely high outlier price that does not reflect the valuation of the broader collection. Therefore, instead of final auction price, the floor price was selected as the primary dependent variable because it represents the standard collection-level pricing metric available on marketplaces like OpenSea. It has also been used as a dependent variable in NFT studies by Borri et al. (2022) and Fridgen et al. (2023), consistent with which, all floor prices were converted from ETH cryptocurrency to U.S. dollars. This was achieved using built-in marketplace currency conversion features available on OpenSea.

The complete variable operationalization is listed in Table 1.

Table 1: *Operationalization of Independent and Dependent Variables*

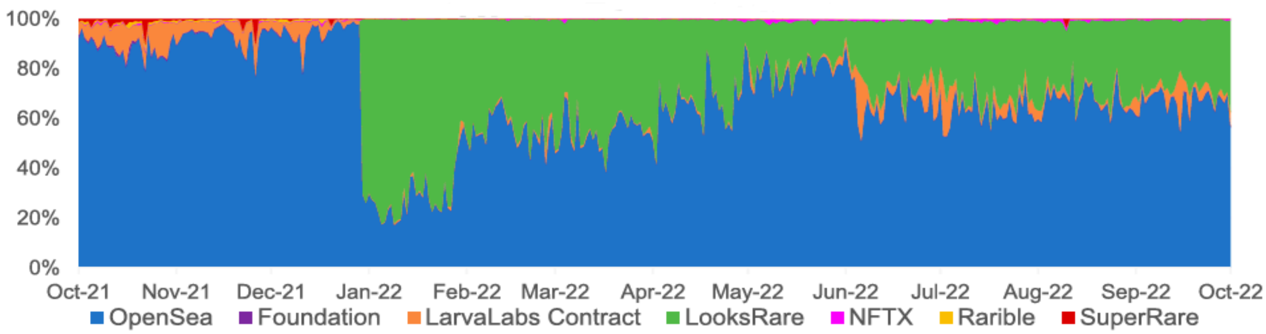
Specific Variable	Measurement/Inclusion Criteria	Data Type
Community Engagement	Number of Discord members	Discrete
Social Visibility	Number of X followers, Instagram followers, and GIPHY views	Discrete
External Validation	Existence of official brand partnerships or public celebrity endorsements/purchases	Binary
Game Assets	Existence of customizable/playable game assets	Binary
Merchandise Integration	Existence of physical/digital apparel and items	Binary
Exclusive Experiences/Features	Existence of concierge perks (premium events/facilities/services/tools/content)	Binary
Valuation	Floor price (USD)	Continuous

Note. The first 6 rows represent the independent variables and the last row represents the dependent variable. These variables were operationalized for all selected collections in the watchlist cohort (*n* = 46).

Selection Criteria

A multi-stage filtering approach was utilized to select the collections on OpenSea, the largest NFT marketplace, as seen in Figure 6 (Kapoor et al., 2022; Zhang et al., 2025).

Figure 6: *NFT Market Share*



Note. Diagram portraying the market share of NFTs from October 2021 to October 2022, with data from the Dune website. Reprinted from *"*Has the fan economy affected the price of non-fungible tokens (NFTs)?*"* by Zhang, J., Cao, Q., & Wen, R., 2025, *Frontiers in Blockchain*, *8* (https://doi.org/10.3389/fbloc.2025.1588837). Copyright 2025 by Zhang, J., Cao, Q., & Wen, R. Licensed under CC BY 4.0 (http://creativecommons.org/licenses/by/4.0/).

While the initial goal was to sample across the six major NFT categories established by Nadini et al. (2021), a preliminary pilot sampling revealed that categories other than "collectibles" are underdeveloped, exhibiting vague trait documentation which did not align with the study's focus on hedonic and utilitarian determinants. Consequently, the scope was narrowed to collectibles or PFP (Profile-Picture) collections, as suggested by OpenSea's standardized categorical taxonomy. PFP collections have also been focused by previous studies due to their "popularity among NFT investors" (Kräussl & Tugnetti, 2023; Szydło et al., 2023).

Next, to preserve data integrity, purposive sampling (Appendix A) was conducted to identify 50 PFP collections — both blue-chip (Appendix A) and non-blue-chip — that satisfied these four objective inclusion criteria:
(i) launched during or after 2021 (for alignment with the post-crypto bubble temporal gap)
(ii) verified "blue-check" projects (for data authenticity and avoiding fraudulent listings)
(iii) operated by official collection accounts across Discord, X, Instagram, and GIPHY (for reliable community engagement and social visibility metrics)
(iv) maintained English-language websites (for accurate trait assessment)

A size of 50 collections ensured research feasibility and relevance given constraints and study objectives. The steps in Figure 7 were followed and cross-checked with the purposive sampling checklist in Table B1, Appendix B (Memon et al., 2025).

Figure 7: *Steps for Implementing Purposive Sampling in Quantitative Research*

Note. All steps above were followed in the order depicted; however, criteria were defined after selecting the sampling type (purposive sampling). To monitor data quality, a rigorous data cleaning process was conducted after the purposive sampling. Reprinted from "Purposive Sampling: A Review and Guidelines for Quantitative Research" by Memon, M. A., Thurasamy, R., Ting, H., & Cheah, J.-H., 2025, *Journal of Applied Structural Equation Modeling*, *9*(1), 1–23 (https://doi.org/10.47263/JASEM.9(1)01). Copyright 2025 by Memon, M. A., Thurasamy, R., Ting, H., & Cheah, J.-H. Licensed under CC BY 4.0 (http://creativecommons.org/licenses/by/4.0/).

Lastly, a rigorous data cleaning process on the purposeful sample was conducted to exclude collections that had either switched social media handles or were managed by company or creator accounts consisting of non-collection-related content. This delimitation avoided deflated/inflated metrics which would have distorted the data.

The complete selection process framework was based on Figure B1, Appendix B (Memon et al., 2025). The final sample consisting of 46 collections was digitally indexed via OpenSea's watchlist feature, and will be referred to as the watchlist cohort (Table B2, Appendix B).

Data Collection

To minimize temporal confounding and account for the high volatility and price fluctuations of the NFT market, data for all 46 collections were collected via a synchronized market snapshot on January 1st, 2026, between 10 a.m. and 1 p.m. Restricting to a narrow three-hour window allowed for stabilized market conditions, maintaining cross-sectional consistency and feasibility. Floor price and trait variables were manually gathered from OpenSea and official collection accounts on Discord, X (formerly Twitter), Instagram, and GIPHY, and triangulated against collection websites. The original descriptive data are recorded in Table B3, Appendix B.

Data Analysis

To reduce high variability and mitigate skewness, the data for community engagement, social visibility metrics, and pricing were log-transformed prior to analysis (Table B4, Appendix B). This aligned with prior literature (Agnello & Pierce, 1996; Borri et al., 2022; Büttner et al., 2022; Elhussein, 2025; Mujtaba, 2025), ensuring the model measures the proportional impact of traits on valuation rather than being biased by outliers. Ultimately, this step standardized the scale across collections in the watchlist cohort for a more accurate comparison.

Next, a Pearson Correlation Matrix of the log-transformed independent variables was generated using Microsoft Excel's built-in Data Analysis ToolPak. Following Zhang et al. (2023) and others, correlations among independent variables were tested to screen for multicollinearity (Appendix A). The correlation results in Table 2 show that all variables are weakly correlated (all coefficients < 0.80), allowing their inclusion in the subsequent regression analysis (Kim, 2019; Zhang et al., 2023). This step reduced the risk of distorted regression (Appendix A) estimates and preserved model validity.

Table 2: *Pearson Correlation Matrix of Log-Transformed Independent Variables*

Independent Variable	*ln* (Discord Memb.)	*ln* (X Foll.)	*ln* (Instagram Foll.)	*ln* (GIPHY Views)	Ext. Valid.	Game Assets	Merch Integ.	Excl. Exp.
ln (Discord Memb.)	1							
ln (X Foll.)	0.233	1						
ln (Instagram Foll.)	0.142	0.1315	1					
ln (GIPHY Views)	-0.068	0.0766	0.093	1				
Ext. Valid.	0.267	0.5856	0.231	0.015	1			
Game Assets	0.425	0.1933	-0.013	0.092	0.392	1		
Merch Integ.	0.323	0.3349	0.269	0.196	0.325	0.195	1	
Excl. Exp.	0.220	0.2004	0.361	0.235	0.609	0.404	0.239	1

Note. Values represent Pearson correlation coefficients. All correlations are below 0.80, indicating weak to moderate associations, and suggesting no multicollinearity issues among the independent hedonic and utilitarian variables included in the hedonic regression analysis. All values are rounded to three decimal digits. Abbreviations: *Memb.* = Members; *Foll.* = Followers; *Ext. Valid.* = External Validation; *Merch Integ.* = Merchandise Integration; *Excl. Exp.* = Exclusive Experiences/Features.

Finally, the hypotheses were tested using the hedonic price regression. While there exist several NFT pricing methods such as repeat sales regression, machine learning, vector autoregression etc., hedonic regression was chosen as it is the predominant model for valuing heterogeneous assets like NFTs (Kräussl & Tugnetti, 2023). Its framework, formalized by Rosen (1974) after building on earlier empirical work by Court (1939), mathematically models the impact of distinct characteristics on asset pricing, effectively linking individual product attributes to value. This aspect proved directly valuable to the study's focus as it can be tied to the collection-level valuation to estimate the isolated price of each recorded trait.

Typically, marginal trait contributions to the price in hedonic regression are estimated using a pure linear ordinary least square (OLS) or logarithmic-linear model (Kräussl & Tugnetti, 2023). For "high tech goods" particularly, the logarithmic-linear model is preferred because it reduces the problem of nonlinearity and heteroscedasticity (Appendix A) in data (Eurostat et al., 2013). Since the raw data in this study exhibited significant scale-dependent variance, the log-linear model was applied using natural log-transformed variables.

The first equation below represents the standard log-linear hedonic pricing model established in foundational literature (Eurostat et al., 2013):

$$\ln\left(p_i^t\right) = \beta_0^t + \sum_{n=1}^{N} \beta_n^t x_{ni}^t + \varepsilon_i^t \tag{1}$$

Since this study captures a specific market snapshot, this second equation presents the simplified cross-sectional version adapted from the above framework (Kräussl & Tugnetti, 2023):

$$\ln\left(p_i\right) = \beta_0 + \sum_{n=1}^{N} \beta_n x_{ni} + \varepsilon_i \tag{2}$$

Finally, the third equation represents the expanded study-specific model for the empirical analysis, incorporating the unique independent variables identified for the watchlist cohort:

$$\begin{aligned}\ln\left(\text{Floor Price}_i\right) = \beta_0 &+ \beta_1 \ln\left(\text{Discord Memb.}_i\right) + \beta_2 \ln\left(\text{X Foll.}_i\right) \\ &+ \beta_3 \ln\left(\text{Instagram Foll.}_i\right) + \beta_4 \ln\left(\text{GIPHY Views}_i\right) \\ &+ \beta_5 \text{Ext. Valid.}_i + \beta_6 \text{Game Assets}_i \\ &+ \beta_7 \text{Merch Integ.}_i + \beta_8 \text{Exc. Exp.}_i + \varepsilon_i\end{aligned} \tag{3}$$

The mathematical notation and parameter definitions used in the equations above are summarized in Table 3, utilizing standard hedonic pricing descriptors adapted from Eurostat et al. (2013) and Kräussl & Tugnetti (2023).

Table 3: *Model Specification and Definition of Mathematical Regression Symbols*

Symbol	Term	Definition/Role in the Hedonic Regression Model
p_i	Price	Floor Price of the NFT collection i (natural log-transformed)
β_0	Intercept	Baseline value of the collections when all other traits are zero
$\sum_{n=1}^{N}$	Summation Operator	Sum of the individual price values added by all different traits from 1 to N, where lower bound = n ; upper bound/total number of traits = N)
β_n	Coefficient	Characteristic parameter; marginal contribution of the trait n
x_{ni}	Regressor	n –th characteristic of the collection i
ε_i	Error Term	Random stochastic error term capturing other factors (white noise) affecting price
t	Time	Time at which the data was collected

Note. Regressors (independent variables) include both continuous regressors (discrete variables) and dummy variables (binary variables). *Trait and characteristic* are used interchangeably and refer to the hedonic and utilitarian valuation determinants.

The log-linear hedonic price regression was performed using the Data Analysis ToolPak add-in within Microsoft Excel to estimate the implicit impact of each identified hedonic and utilitarian trait on the collection-level NFT floor price valuation.

RESULT

Before examining individual predictors, it is crucial to evaluate the resulting model's overall performance. As seen in Table 4, the model demonstrated a robust fit, explaining more than half of the variance in floor prices (R^2 = 0.601, Adjusted R^2 = 0.515). Notably, this explanatory power exceeds the fit reported in similar NFT valuation studies; for instance, Ziemke et al. (2023) achieved a highest reported R^2 of 0.385. The fact that this study's Adjusted R^2 surpasses the standard R^2 of previous models suggests the selected combination of independent variables provides a comprehensive framework for understanding price fluctuations in an otherwise speculative market.

Table 4: *Summary of Regression Statistics for the NFT Valuation Model*

Statistic	Value
Multiple R	0.775
R^2	0.601
Adjusted R^2	0.515
Standard Error	1.675
n	46

Note. The R^2 and Adjusted R^2 values indicate that approximately 60.1% and 51.5% of the variance in NFT floor prices can be explained by the independent variables included in this model. All values are rounded to three decimal digits.

Additionally, the ANOVA results in Table 5 indicate that the regression is statistically significant, F (8, 37) = 6.961, p < .001. Since p is substantially lower than the significance level (.05), this also confirms that the included trait predictors outperformed an intercept-only model.

Table 5: *ANOVA (Analysis of Variance) Results for the Multivariate Hedonic Regression*

Source	df	SS	MS	F	p
Regression	8	156.225	19.528	6.961	< .001
Residual	37	103.797	2.805		
Total	45	260.022			

Note. The F (8, 37) = 6.961 is significant at the p < .001 level, indicating that the regression model and the remaining residual (error) variance reliably predict the dependent variable of collection-level NFT floor price valuation. All values are rounded to three decimal digits.

A detailed breakdown of the coefficients and *p* values for each independent variable is provided in Table 6. As visible, the coefficients for '*ln* (Discord Members),' '*ln* (X Followers),' 'External Validation,' 'Game Assets,' and 'Merchandise Integration' are positive, indicating a direct relationship where for each unit increase in these variables, the floor price also rises. Looking at the strength of the respective coefficients, a 1% increase in 'Discord Members' is associated with a 0.12% increase in the NFT floor price. By extension, this also means that a 100% increase in 'Discord Members' is associated with a 12% increase in floor price. Similarly, every 1% increase in the number of X followers corresponded to a 0.279% increase in floor price. Surprisingly, '*ln* (Instagram Followers),' '*ln* (GIPHY Views),' and 'Exclusive Experiences/Features' yielded negative coefficients, implying an inverse relationship where the presence or growth of these variables correlates with a decrease in floor price. For example, an increase of 1% in '*ln* (Instagram Followers)' resulted in a decrease 0.085% in floor price as demonstrated by its resultant coefficient. Likewise, a 1% increase in the variable '*ln* (GIPHY Views)' correlated with a change of -0.003% in floor price. In terms of statistical reliability, only '*ln* (Discord Members)' and 'External Validation' were significant at the 5% level ($p < .05$), suggesting they are the most credible predictors in the model. Other independent variables such as '*ln* (X Followers),' 'Merchandise Integration,' and 'Exclusive Experiences/Features' had marginal significance at the 10% level ($p < .10$), identifying them as secondary factors determining valuation. The remaining traits of '*ln* (Instagram Followers),' '*ln* (GIPHY Views),' and 'Game Assets' lacked the statistical strength to be considered meaningful drivers of floor price.

Table 6: *Regression Coefficients and Significance Levels of the Valuation Determinants*

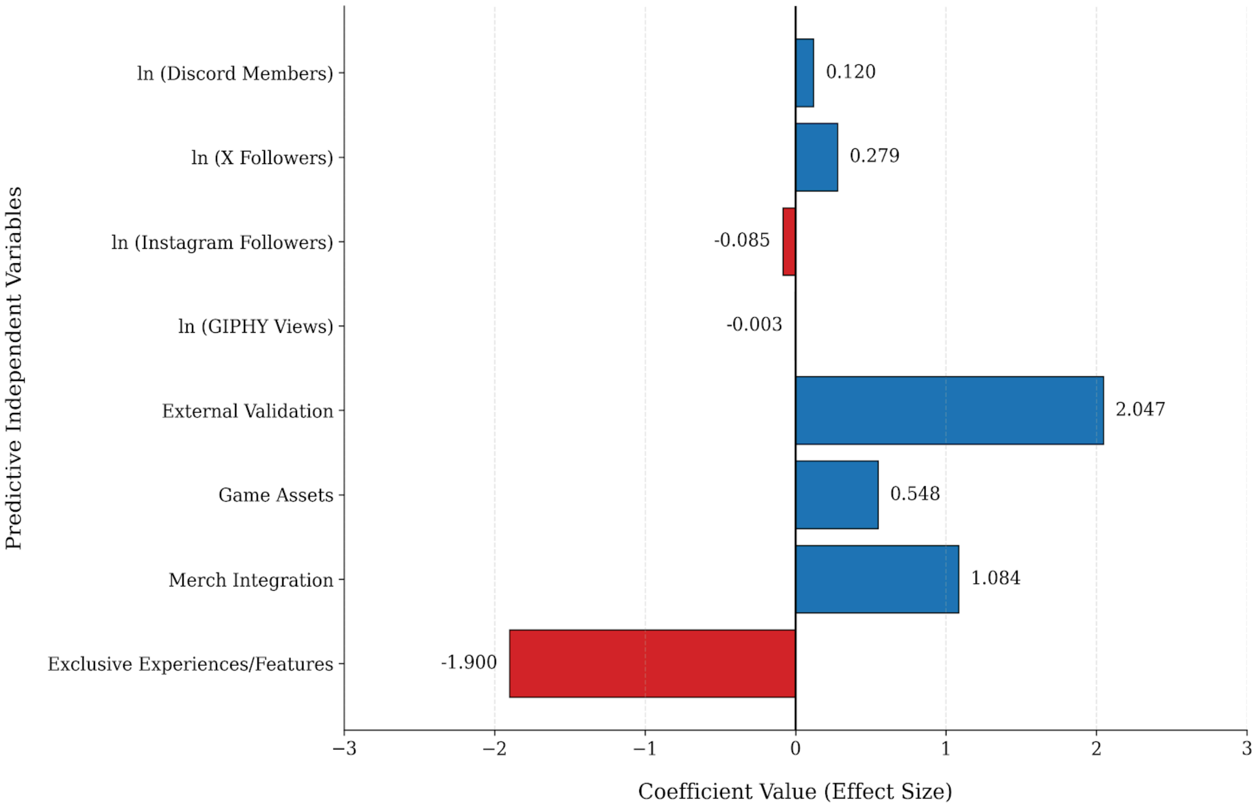
Independent Variable	Coefficients (β)	*SE*	*t Stat*	*p values*	Lower 95%	Upper 95%
Intercept	0.789	1.528	0.516	.609	-2.308	3.885
ln (Discord Memb.)	0.120	0.059	2.037	.049**	0.001	0.240
ln (X Foll.)	0.279	0.144	1.938	.061*	-0.013	0.571
ln (Instagram Foll.)	-0.085	0.051	-1.675	.102	-0.187	0.018
ln (GIPHY Views)	-0.003	0.029	-0.093	.927	-0.061	0.055
Ext. Valid.	2.047	0.867	2.361	.024**	0.290	3.804
Game Assets	0.548	0.624	0.878	.386	-0.716	1.812
Merch Integ.	1.084	0.578	1.877	.069*	-0.086	2.255
Excl. Exp.	-1.900	1.014	-1.874	.069*	-3.955	0.155

Note. The dependent variable is the natural log of the NFT collection floor price, *ln* (Floor Price). Significant predictors are indicated by asterisks: *$p < .10$ (marginally significant), **$p < .05$ (significant). All values are rounded to three decimal digits. Abbreviations: *Memb.* = Members; *Foll.* = Followers; *Ext. Valid.* = External Validation; *Merch Integ.* = Merchandise Integration; *Excl. Exp.* = Exclusive Experiences/Features.

Among the predictors, 'External Validation' exhibited the highest statistical significance and greatest positive correlation with valuation ($p = .024$, β: 2.047) as visualized in Figure 8. Its presence led to a

2.047 increase in *ln* (Floor Price), holding all other variables constant. Interestingly, Exclusive Experiences/Features had a large negative coefficient (β: -1.900), where every unit increase led to a decrease of 1.900 in *ln* (Floor Price).

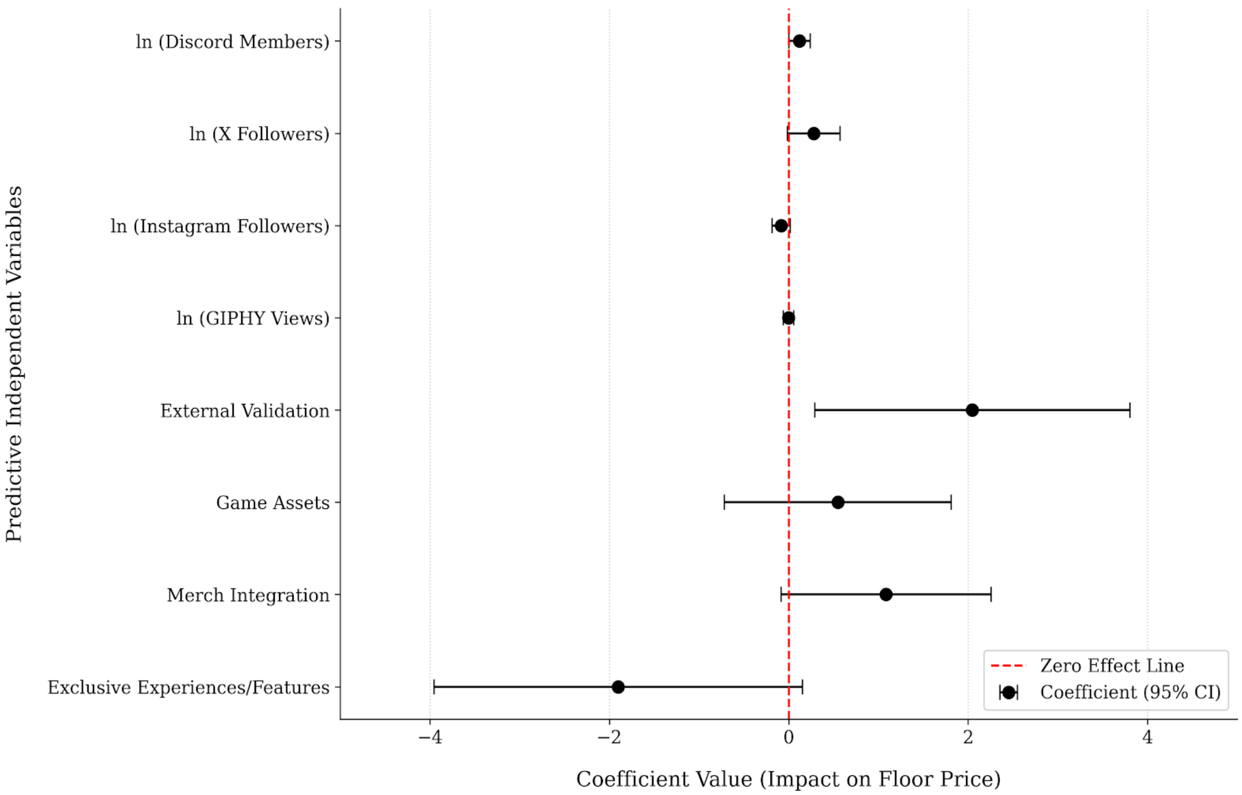
Figure 8: *Comparison of Relative Impact of of Independent Variables on NFT Collection Floor Price*



Note. Horizontal bar graph representing the magnitude and direction of the effect of each independent predictive variable (measured by coefficient value) on the natural log of the NFT collection floor price, *ln* (Floor Price). Blue bars indicate a positive (direct) relationship, while red bars indicate a negative (inverse) relationship. All coefficient values are rounded to three decimal digits.

Figure 9 illustrates the 95% confidence intervals constructed using reported values in Table 6. Confidence intervals represent the range of plausible values for each price coefficient, and as visible, only External Validation demonstrates an interval entirely excluded from zero, reinforcing its reliability as a robust positive valuation determinant. While variables like *ln* (Discord Members), '*ln* (X Followers), and Merchandise Integration also have statistically significant positive results at the 5% and 10% levels respectively (p = .049, p = .061, p = .069), their confidence intervals either sit extremely close to the null line or overlap it. Thus, their price influence is modest compared to External Validation which remains positive even at its lower bound. Notably, despite its strength, External Validation's wide interval suggests greater variance in market impact. This highlights that while its effect is consistently positive, the exact magnitude of its influence fluctuates across different collections.

Figure 9: *Forest Plot of Regression Coefficients for NFT Valuation Predictors (95% Confidence Interval)*



Note. Forest plot visualizing point estimates for the regression coefficients (black dots) and their corresponding 95% confidence intervals (horizontal bars). The 95% confidence interval estimates (lower and upper bounds) are obtained from the regression results reported in Table 6. The red dashed line denotes the zero effect (null hypothesis) line. Independent variables with intervals that do not intersect/cross the zero effect line (i.e., remain entirely on one side of zero) are interpreted as statistically significant at the $p < .05$ level.

DISCUSSION

Results yielded partial support for Hypothesis 1 — only four of the eight modeled variables demonstrated a statistically significant positive relationship with floor price at the 5% and 10% levels (Table 2). This indicates matured investor discernment in the post-hype market as not every additional NFT feature automatically translates to a perceived value-add. '*ln* (Discord Members)' and '*ln* (X Followers)' had a significant positive correlation with floor price, aligning with Zhang et al. (2025) who used HDFE regression to obtain the same relationship at the 1% level. This supports their finding that the social media "fan economy" boosts prices, suggesting that both community depth through active fans and broader reach through passive followers matter. However, Zhang and colleagues did not measure the impact of Instagram followers, which showed no significant relationship with valuation in this study. This challenges the generalizability of their conclusion and indicates the follower effect may be more nuanced than previously thought, likely not applying uniformly across all social platforms. The novel variable '*ln* (GIPHY Views)' was also not significant (p = .927); perhaps social visibility is platform-dependent and limited to NFT-centric networks like Discord / X. Additionally, 'Merchandise Integration' showed a significant positive trend, supporting Colicev's (2022) example of brands leveraging physical-digital products to drive sales. However, not "any [all] added utility" was positively associated with valuation as assumed by Brandes & Dölp (2025). The presence of the marginally significant trait 'Exclusive Experiences/Features' had a large negative impact on floor price. Conceivably, in a market cautious of scams, exclusive utility services and concierge perks might be viewed skeptically by investors. 'Game Assets' was also not a significant predictor, differing from Li et al. (2025) who found that NFT gamification can lend brands a comparative advantage. Consequently, these varying findings suggest that NFT valuation benchmarks are highly contextual, rather than applying uniformly across different collection categories.

Finally, 'External Validation' emerged as the most significant positive predictor of collection-level valuation among all variables (p = .024, β: 2.047), qualifying Hypothesis 2. The high coefficient suggests a hierarchical value-driving capacity among NFT features, where specific signals exert disproportionate influence. Thus, in the post-bubble phase, investors rely on Signaling Theory to mitigate transparency risk; third-party assurance — through brand partnerships and celebrity endorsements — acts as a trust signal which hedges against the volatile, information-asymmetric NFT market (Zhang et al., 2026). Indeed, collections with strong mainstream legitimacy like BAYC (celebrity-backed by Justin Bieber, Eminem, Jimmy Fallon among others) and Pudgy Penguins (featured on the Las Vegas Sphere, partnered with Walmart/Amazon) held some of the highest recorded floor prices. Clearly, even though celebrity endorsements and brand partnerships do not signal expertise credibility, they reflect the social hype and public trust which drives up NFT collection demand. Ultimately, their external validation is what translates directly into higher valuations for collections.

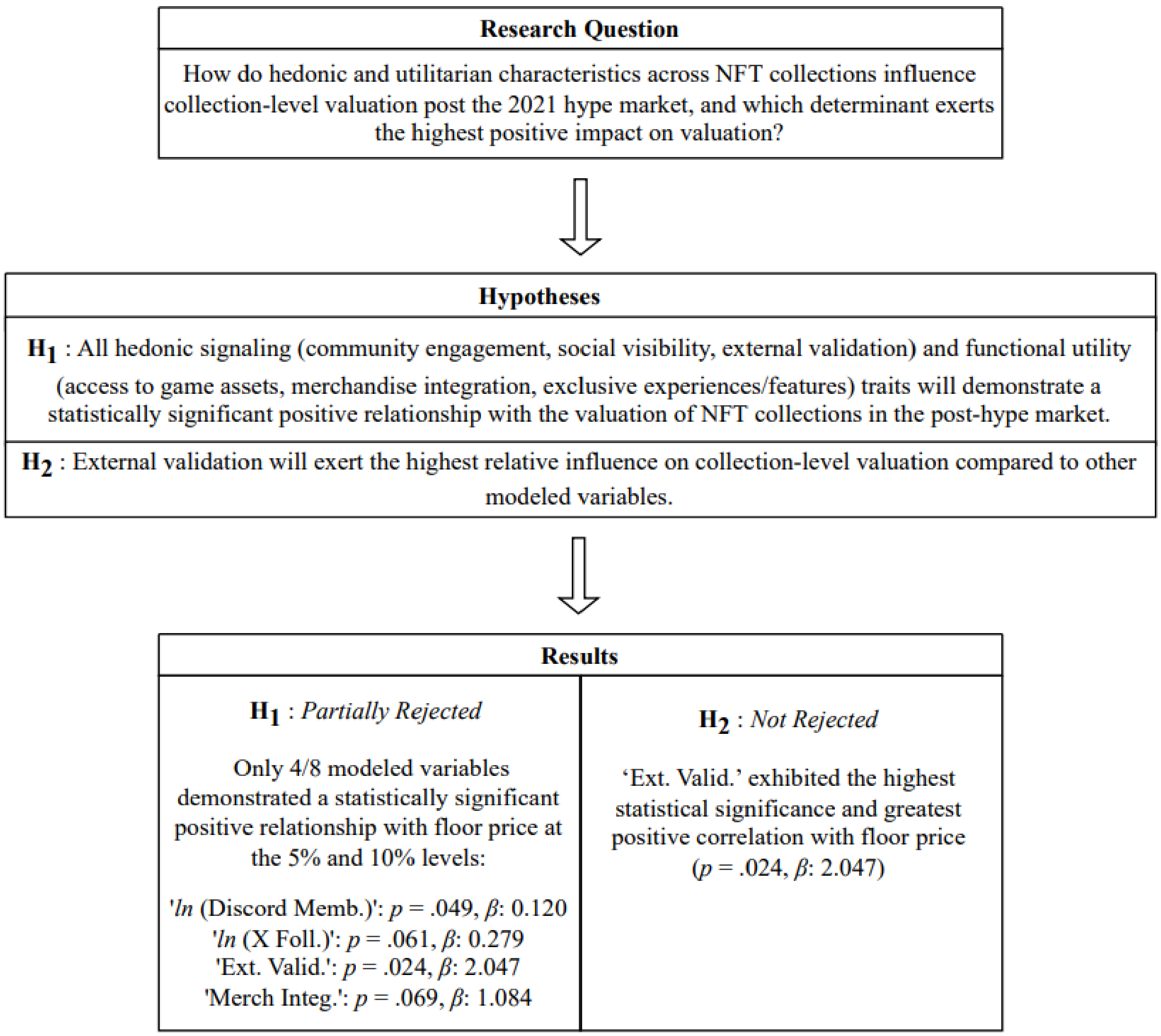
Limitations

Nevertheless, some study limitations must be acknowledged. The temporal delimitation to collections launched during/after 2021 excluded pioneer collections that still influence broader market sentiment. Also, the purposive sampling approach — while intentional for accuracy — filtered several collections, leading to a small sample size (n = 46). This provided limited data and is a key reason why the model only explained 60.1% of the variance in floor price. However, the discrepancy also stems from constraints of the hedonic regression itself, as Borri et al. (2022) emphasize that independent variables in hedonic NFT models may be arbitrary and incomplete due to the heterogeneous nature of collections. For instance, aesthetic appeal was excluded as a variable because it is subjective and inherently non-quantifiable. Additionally, due to insufficient data to count the number of gaming features across collections, game assets were limited to a binary indicator rather than a numerical count. There exists a further risk of including irrelevant variables, which might not impact the dependent variable as assumed (Kräussl & Tugnetti, 2023). Moreover, the cross-sectional method design restricted understanding of data composition over time. Lastly, floor price failed to capture the wash trading (fake volume) and insider sales that often inflate OpenSea stats (Wang et al., 2025).

CONCLUSION

This causal-comparative study used hedonic regression to estimate the impact of hedonic and utilitarian characteristics on collection-level NFT valuation. It contributes to existing literature by redefining various traits as quantifiable pricing factors, and addressing critical research gaps. Figure 10 illustrates the alignment of the research question, hypotheses, and results.

Figure 10: *Alignment of Research Question, Hypotheses, and Empirical Results*



Note. Summary chart aligning the research question, tested hypotheses, and resulting statistical outcomes. The "Results" column details the specific performance of modeled variables that satisfied the hypotheses, reporting their p-values (p) and beta coefficients (β) to indicate their significance and direction of impact on *ln* (Floor Price). All values are rounded to three decimal digits. Abbreviations: *Memb.* = Members; *Foll.* = Followers; *Ext. Valid.* = External Validation; *Merch Integ.* = Merchandise Integration.

Implications

Results may guide NFT creators and brands to strategically leverage community engagement, social media visibility, merchandise-utility, and external validation when designing collections. Particularly, external validation should be focused on as it acts as a powerful “trust signal” which triggers investor interest; when a collection is perceived as credible, it may create a stable, coordinated equilibrium where demand becomes self-reinforcing (Appendix A). For collectors, investing in credible collections with strong communities might mitigate risk and increase profits. They may also benefit by using these findings to predict market trends, identify speculative excess, diversify portfolios, and make more informed investment choices. Additionally, these insights can strengthen post-bubble NFT valuation frameworks, allowing marketplaces, issuers, and regulators to better adjust pricing and enhance buyer confidence (Zhang et al., 2025). Finally, the data can support policy and institutional understanding, encouraging broader participation and transparency in the illiquid NFT market (Appendix A).

Future Directions

The study’s limitations are catalysts to future research. A longitudinal study could be conducted to observe changes over time with a larger sample. Specifically, the Bayesian dynamic hedonic regression can be used to improve the static model by capturing time-varying coefficient shifts in the NFT ecosystem where trends change quickly (Garay et al., 2022). Scholars can also expand the generalizability of findings by including data from OpenSea’s competing marketplaces and non-PFP collections. In addition, standardized metrics could be developed to move beyond binary indicators and evaluate how the specific number and types of gaming features and merchandise items within a collection influence valuation. Successive research may also perform an analysis of heterogeneity to evaluate how the explanatory power of each hedonic and utilitarian factor changes across distinct NFT categories (Art, Games, Metaverse, Utility). Moreover, the use of GIPHY views as a metric for visual virality is a novel approach which can be further examined along with external validation. A study investigating the "Lindy Effect" to observe whether pioneer NFT collections with first-mover advantage hold value better than new ones would also provide valuable insight into long-term sustainability.

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APPENDIX A: Glossary of Key Terminology

Blue-chip collection: Blue-chip collections are collections of high-value, historically significant artworks by established artists whose work is consistently in demand and retains value, analogous to "blue-chip" stocks in finance (*Blue-Chip Contemporary Art*, 2025).

Boom-bust dynamic: Boom-bust dynamic refers to rapid price runups followed by steep declines (Benhima, 2019).

Bubble: Financial bubbles occur when asset prices inflate far above their fundamental value due to investor speculation, overly optimistic expectations, and herd behavior, followed by a sharp crash once market sentiments shift (*Asset Price Bubbles*, 2024). This study situates the 2021 crypto bubble within that context.

Bull market: Bull market describes a period when asset prices are rising or expected to rise, reflecting investor optimism and strong demand; the opposite of a bear market (Hayes, 2019).

Causal-comparative analysis: A causal-comparative analysis seeks to identify relationships between independent and dependent variables after an action or event has already occurred. The researcher's goal is to determine whether the independent variable affected the outcome (dependent variable) by comparing two or more groups without manipulating the variables (Salkind et al., 2010).

Concierge perks: While the term 'concierge perks' lacks a formal definition in economic literature, industry usage (The NFT Buzz, 2024) describes it as a utilitarian NFT feature that provides holders with personalized, premium, or priority services from the issuing brand/collection, such as dedicated support, exclusive event access, VIP experiences, or tailored product assistance. These services increase perceived value and are designed to go beyond basic ownership to offer exclusive real-world benefits and assistance to NFT holders.

Consumer Culture Theory (CCT): Consumer Culture Theory is an interdisciplinary field that examines the social and cultural meanings behind consumption rather than just the rational economic utility of products. It explores how individuals use consumption as a tool for identity construction, social signaling, and navigating hierarchies within various subcultures (Mercadal, 2021).

Consumer Theory: Consumer Theory is a branch of microeconomics that analyzes how individuals make choices to spend their limited resources based on their preferences and budget constraints. It focuses on how consumers aim to achieve "utility maximization" by selecting a combination of goods that provides the greatest possible satisfaction (Liberto, 2023).

Coordinated equilibrium: A coordination equilibrium is a situation in a coordination game such that no player benefits from unilaterally changing their strategy. In this equilibrium, players' payoffs depend on successfully matching or aligning their choices with the decisions of others. In the context of this study, a coordination equilibrium occurs when investors collectively converge on purchasing or holding NFTs from the same collection because everyone benefits from aligning their actions (Vanderschraaf & Sillari, 2023).

Cross-sectional design: A cross-sectional research design seeks to gather data at a single point in time to obtain a "snapshot" or picture of a unit of analysis. This design assumes that the population under study is heterogeneous in its characteristics, aiming to properly represent the diversity and varied behaviors within the group (Lewis-Beck et al., 2004)

Diversification: Diversification is a risk management strategy that spreads investments or operations across various assets, industries, or markets to reduce the impact of any single underperforming asset, increase stability, and optimize returns (Koumou, 2020).

Endowment bias: Endowment bias is the tendency for investors to value an asset they have bought or inherited more highly than an identical asset they do not own, simply because of ownership (Sukhani, 2025).

Extrinsic motivation: Extrinsic motivation defines the propensity to perform an activity to obtain external rewards or avoid negative outcomes (Griffiths et al., 2024). For NFT buyers, extrinsic motivation reflects interest driven by potential financial profits, public visibility, or status.

Hedonic: Hedonic refers to "emotion rich" attributes that appeal to intrinsic motivation, personal desire, aesthetics, emotional engagement, and status signals (Adriana et al., 2024). In the context of financial markets, hedonic characteristics influence pricing by increasing perceived desirability.

Hedging: Hedging refers to strategies or features that reduce downside risk (*Financial Hedging | EBSCO*, 2021).

Heteroscedasticity: Heteroscedasticity refers to the "non-constant variance of the errors." Essentially, it is a situation in a regression model where the variance of the residuals (the "errors" or the difference between the observed value and the predicted value) is not constant across all levels of an independent variable. This leads to unreliable standard errors and p-values in the OLS regression because equal weight is given to all observations, even though the error terms for larger-scale variables are much greater (Eurostat et al., 2013)

Heterogeneous: Heterogeneous describes a market composed of widely varying asset types and investor motives. In the context of NFTs, heterogeneous refers to the diverse and varied characteristics present within NFT collections (Mekacher et al., 2022).

Idiosyncratic volatility: Idiosyncratic volatility refers to asset-specific price swings not explained by market moves (Ummuhani & Abdussalam, 2025).

Intrinsic motivation: Intrinsic motivation describes the internal drive to engage in an activity for personal satisfaction, enjoyment, or interest, rather than for external rewards (Griffiths et al., 2024). In the context of NFTs, intrinsic motivation reflects buyers' engagement due to curiosity, aesthetic appreciation, or personal fulfillment.

Intrinsic value: Intrinsic value captures an asset's inherent true worth based on its fundamental hedonic and utilitarian characteristics as opposed to price defined by market (Ashburn, 2025; Hofstetter et al., 2024). In the context of NFTs, it refers to the value derived from attributes like rarity, artistic quality, creator reputation, or real-world utility independent of speculative demand.

Investment stability: Investment stability describes the capacity of financial systems and markets to maintain resilience by absorbing economic shocks and resolving financial imbalances effectively (European Central Bank, 2023). It measures the persistence of value over time, reflecting lower idiosyncratic volatility.

Liquidity: Liquidity refers to the ease of converting a non-cash asset (like NFT) into cash for buying and selling without a large price impact on the asset (Montevirgen, 2025; Naik & Reddy, 2021).

Multicollinearity: Multicollinearity occurs when two or more independent variables are highly correlated, meaning one variable can be largely predicted from the others. Even strong, non-exact correlations are sufficient to cause multicollinearity issues in regression analysis (Kim, 2019).

NFT (Non-Fungible Token): An NFT is a unique digital asset typically minted on the Ethereum blockchain (using the ETH cryptocurrency). Unlike "fungible" or interchangeable cryptocurrencies such as Bitcoin, NFTs cannot be exchanged on a one-to-one basis. Each token is individually identifiable and ownership is cryptographically verifiable, meaning blockchain technology allows secure proof of authenticity, provenance, and exclusive control over the NFT (Kräussl & Tugnetti, 2023).

Purposive sampling: Purposive sampling, also known as judgmental or selective sampling, is a non-probability sampling technique in which cases are intentionally selected based on predefined criteria relevant to the study and the researcher's prior knowledge. Unlike random sampling, this method focuses on identifying "information-rich" cases that align specifically with the research objectives to improve precision and validity (Bullard, 2024; Memon et al., 2025). In this study, purposive sampling was utilized to ensure the selected NFT collections possessed clear, credible, and necessary market data required for a granular analysis of hedonic and utilitarian traits.

Regression: Regression is a statistical tool used to build a model that estimates quantitative relationships between one or more independent variables and a dependent variable (Brdesee & Alsaggaf, 2021). In this study, the hedonic price regression model is applied to estimate relationships between collection-level NFT traits and valuation.

Secondary market: Secondary market is a platform where previously issued assets are resold between buyers and sellers rather than sold for the first time by the original creator or issuer (Sweeting, 2019).

Signaling Theory: Signaling Theory explains behavior in market environments where there is information asymmetry between a sender (the project) and a receiver (the buyer). It posits that to reduce uncertainty and prove quality, senders must provide observable, high-cost "signals" that are difficult for low-quality competitors to replicate (*Signaling Theory - an Overview | ScienceDirect Topics*, n.d.). Some signaling examples include pricing, money-back guarantees, hassle-free return insurance, third-party certification and assurance, advertising, among others (Zhang et al., 2026). This study focuses on signaling through third-party assurance, specifically through brand partnerships and celebrity endorsements.

Social value: Social value captures the "approval or interpersonal connection" associated with an asset (Hofstetter et al., 2024). For NFTs, this includes network effects, visibility, and community buzz that amplify demand.

Utilitarian: Utilitarian refers to "cognition-based" attributes that are driven by extrinsic motivation and necessity rather than desire (Adriana et al., 2024). These provide functional utility, such as access rights, platform services, governance, security, ecosystem integration, and perceived price-value. In financial markets, utilitarian characteristics influence pricing by enhancing practical value or usability.

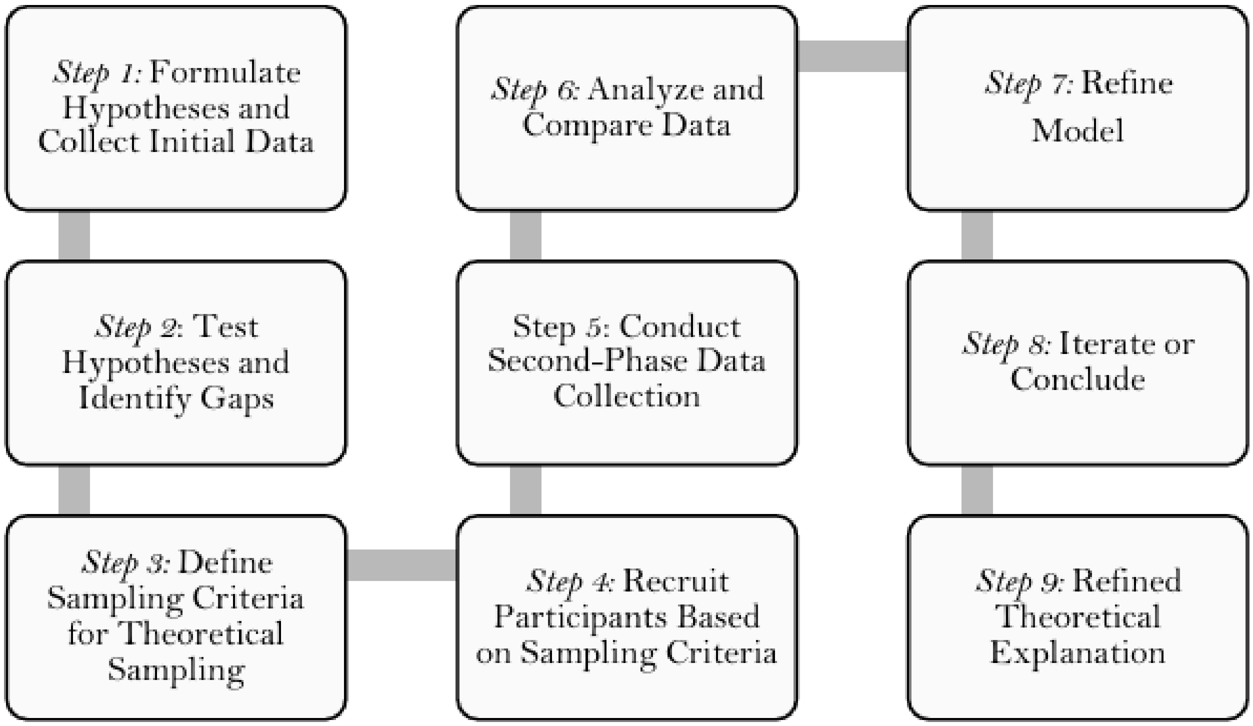
APPENDIX B: Supplementary Methodology Data Tables and Procedural Documentation

Table B1: *Checklist for Reporting Purposive Sampling in Quantitative Research*

Item	Description	✔
Justification for Sampling Method	Does the manuscript clearly explain the rationale for using purposive sampling and its alignment with the study's quantitative objectives?	☐
	If purposive sampling was combined with other methods, does the manuscript justify how the combination enhances data collection and analytical rigor?	☐
	Is the choice of purposive sampling supported by relevant literature, demonstrating its suitability for the study's context and research questions?	☐
Criteria for Respondent Selection	Are the participant selection criteria explicitly defined and directly tied to the research objectives or hypotheses?	☐
	Does the manuscript provide a clear explanation of how the criteria ensure the inclusion of participants relevant to the study's analytical needs?	☐
	Are the criteria grounded in existing literature or logically justified, particularly if they are unique or exploratory in nature?	☐
Detailed Sampling Procedure	Does the manuscript describe, step-by-step, how participants were identified, contacted, and recruited, ensuring transparency in the process?	☐
	Are the tools or sources used for identifying participants (e.g., professional directories, networks, websites, indexes etc.) and the rationale for their use clearly explained?	☐
	Does the manuscript document any adjustments made during the sampling process to address gaps or imbalances in the sample composition?	☐
Sample Size Justification and Power Analysis	Is the sample size justified based on the study's analytical requirements and the purposive nature of the sampling strategy?	☐
	Does the manuscript explain how the sample size ensures sufficient representation of key subgroups or characteristics critical to the research objectives?	☐
	Are potential constraints, such as limited participant availability, addressed in the justification for the sample size?	☐
Final Sample Characteristics	Does the manuscript provide a concise summary of the final sample's key characteristics, such as demographics, professional roles, or other attributes relevant to the study?	☐
	Are any imbalances in the sample composition acknowledged, and their implications for the study's findings discussed?	☐
	Are subgroup characteristics clearly reported when the research involves comparisons or stratified analyses?	☐
Limitations and Biases in Sampling	Does the manuscript explain how informed consent and confidentiality were maintained throughout the sampling process?	☐
	Are ethical challenges specific to purposive sampling (e.g., selection bias or exclusivity) transparently addressed?	☐
Literature Support	Has relevant literature been cited to support each aspect of the sampling process, from the choice of method to criteria justification, sample size, and ethical practices?	☐

Note. All criteria listed above were strictly applied during the purposive sampling process. Reprinted from "Purposive Sampling: A Review and Guidelines for Quantitative Research" by Memon, M. A., Thurasamy, R., Ting, H., & Cheah, J.-H., 2025, *Journal of Applied Structural Equation Modeling*, *9*(1), 1–23 (https://doi.org/10.47263/JASEM.9(1)01).

Figure B1: *Theoretical Sampling Process in Quantitative Research*



Note. All nine steps listed above were followed. The initial data collection in Step 1 corresponds to the preliminary pilot sampling within this study's process. Reprinted from "Purposive Sampling: A Review and Guidelines for Quantitative Research" by Memon, M. A., Thurasamy, R., Ting, H., & Cheah, J.-H., 2025, *Journal of Applied Structural Equation Modeling*, *9*(1), 1–23 (https://doi.org/10.47263/JASEM.9(1)01). Copyright 2025 by Memon, M. A., Thurasamy, R., Ting, H., & Cheah, J.-H. Licensed under CC BY 4.0 (http://creativecommons.org/licenses/by/4.0/).

Table B2: *Sampling Frame: Watchlist Cohort of Selected NFT Collections (n = 46)*

Collection Name	Launch Year	Collection Name	Launch Year
Azuki	2022	Lonely Aliens	2021
BASED Minis	2024	Lucky Ducky	2022
BAYC	2021	Lucky Sloths	2021
BEANZ Official	2022	MeeBits	2021
Boss Beauties	2021	Memeland Potatoz	2022
Bozo	2025	Milady Maker	2021
Chimpers	2022	Mocaverse	2023
Cool Cats	2021	Moki Genesis	2025
Coolman's Universe	2021	Moonbirds	2022
Creatures	2021	Neiro Woofer Pack	2025
CyberBrokers	2022	Nouns	2021
CyberKongz	2021	PhantaBear	2025
Deez Nuts	2021	Piggy Palz	2021
DeGods	2023	Pudgy Penguins	2021
Dino Gotchis	2025	Quirkies Original	2022
Doodles	2021	Rexy	2025
Ethereans Official	2021	Robotos	2021
Forgotten Runes	2021	Sappy Seals	2021
Fox Fam	2021	Sproto Gremlins	2023
Fugz	2025	The Dreamers	2021
Invisible Friends	2021	The Plushies	2023
Kanpai Pandas	2022	VeeFriends	2021
Lazy Lions	2021	World of Women	2021

Note. The collections included in the watchlist cohort are organized in alphabetical order, not the order in which they were sampled.

Table B3: *Original Descriptive Data for the Watchlist Cohort (Raw Values)*

Collection Name	Discord Memb.	X Foll.	Instagram Foll.	GIPHY Views	Ext. Valid.	Game Assets	Merch Integ.	Excl. Exp.	Floor Price (USD)
Azuki	78,359	442,300	249,000	0	1	1	1	1	$1,880.41
BASED Minis	417	6,000	0	96,300,000	0	0	0	1	$8.66
BAYC	177,504	1,000,000	0	0	1	1	1	1	$13,100.00
BEANZ Official	0	442,300	0	95,700,000	1	1	1	1	$103.96
Boss Beauties	21,907	65,400	15,600	0	1	0	1	1	$14.64
Bozo	0	11,500	0	4,700,000	0	0	1	0	$2.38
Chimpers	28,695	66,300	0	0	1	1	1	1	$1,416.16
Cool Cats	77,597	228,200	81,700	779,700,000	1	1	1	1	$448.27
Coolman's Universe	19,797	126,900	2,700,000,000	0	1	0	1	1	$34.95
Creatures	0	62,100	13,000	0	1	0	0	1	$26.89
CyberBrokers	13,691	38,700	661	0	1	1	0	1	$75.30
CyberKongz	48,879	322,800	3,395	338,800,000	1	1	1	1	$3,564.48
Deez Nuts	0	21,400	58	159,100,000	1	1	0	1	$0.30
DeGods	4,599	198,700	0	0	1	0	1	1	$586.83
Dino Gotchis	45,306	81,200	0	0	0	1	0	1	$18.35
Doodles	81,755	556,500	0	1,700,000,000	1	1	1	1	$1,104.97
Ethereans Official	0	5,380	429	69,500,000	0	0	0	1	$2.39
Forgotten Runes	75,534	115,200	0	0	1	1	0	1	$265.23
Fox Fam	8,311	20,500	1,027	13,800,000	0	1	1	1	$18.19
Fugz	4,850	16,100	0	0	0	0	0	0	$138.75
Invisible Friends	122,237	459,900	117,000	0	1	0	1	1	$191.55
Kanpai Pandas	7,055	47,200	0	202,200,000	1	1	1	1	$188.87
Lazy Lions	110,508	100,700	25,600	0	1	1	1	1	$141.77
Lonely Aliens	0	26,200	4,225	0	0	1	1	1	$17.32
Lucky Ducky	0	12,300	3,930	633,000,000	0	0	0	1	$1.46
Lucky Sloths	2,034	4,606	859	388,800,000	0	0	1	1	$2.39

Collection Name	Discord Memb.	X Foll.	Instagram Foll.	GIPHY Views	Ext. Valid.	Game Assets	Merch Integ.	Excl. Exp.	Floor Price (USD)
MeeBits	8,051	46,400	0	13,900,000	1	1	0	1	$1,196.17
Memeland Potatoz	142,556	2,200,000	38,800	0	1	1	0	1	$223.86
Milady Maker	16,010	13,100	0	0	1	1	1	1	$3,450.45
Mocaverse	0	524,900	0	1,800,000	1	1	0	1	$791.20
Moki Genesis	36,816	70,500	0	0	1	1	0	1	$110.28
Moonbirds	12,838	241,400	0	0	1	1	1	1	$4,314.75
Neiro Woofer Pack	0	68,600	0	0	1	0	0	1	$39.61
Nouns	0	82,200	0	0	1	0	1	1	$1,614.34
PhantaBear	0	53,400	9,879	0	1	1	1	1	$43.22
Piggy Palz	0	847	0	0	0	0	0	0	$8.73
Pudgy Penguins	169,345	709,900	2,000,000	70,300,000,000	1	1	1	1	$12,200.00
Quirkies Original	44,241	58,200	0	0	0	1	1	0	$1,621.88
Rexy	0	211,400	0	0	0	0	0	0	$62.40
Robotos	0	52,400	4,850	0	1	1	0	1	$18.89
Sappy Seals	19,573	99,400	0	3,600,000,000	1	1	1	1	$352.53
Sproto Gremlins	0	12,500	0	0	0	0	0	0	$470.99
The Dreamers	5,640	0	762	0	0	1	0	1	$5.36
The Plushies	7,047	45,800	0	0	0	0	0	0	$113.51
VeeFriends	0	247,400	244,000	5,300,000,000	1	0	1	1	$3,583.77
World of Women	59,043	195,800	275,000	4,200,000	1	1	1	1	$415.09

Note. These cell values represent the original, non-transformed data for the sampled NFT collections in the watchlist cohort. These collections are organized in alphabetical order, not the order in which they were sampled. Abbreviations: *Memb.* = Members; *Foll.* = Followers; *Ext. Valid.* = External Validation; *Merch Integ.* = Merchandise Integration; *Excl. Exp.* = Exclusive Experiences/Features.

Table B4: *Log-transformed Descriptive Data for the Watchlist Cohort*

Collection Name	*ln* (Discord Memb.)	*ln* (X Foll.)	*ln* (Instagram Foll.)	*ln* (GIPHY Views)	Ext. Valid.	Game Assets	Merch Integ.	Excl. Exp.	*ln* (Floor Price)
Azuki	11.269	13.000	12.425	0	1	1	1	1	7.540
BASED Minis	6.035	8.700	0	18.383	0	0	0	1	2.268
BAYC	12.087	13.816	0	0	1	1	1	1	9.480
BEANZ Official	0	13.000	0	18.377	1	1	1	1	4.654
Boss Beauties	9.995	11.088	9.655	0	1	0	1	1	2.750
Bozo	0	9.350	0	15.363	0	0	1	0	1.218
Chimpers	10.265	11.102	0	0	1	1	1	1	7.256
Cool Cats	11.259	12.338	11.311	20.474	1	1	1	1	6.108
Coolman's Universe	9.893	11.751	21.717	0	1	0	1	1	3.582
Creatures	0	11.037	9.473	0	1	0	0	1	3.328
CyberBrokers	9.525	10.564	6.495	0	1	1	0	1	4.335
CyberKongz	10.797	12.685	8.130	19.641	1	1	1	1	8.179
Deez Nuts	0	9.971	4.078	18.885	1	1	0	1	0.262
DeGods	8.434	12.200	0	0	1	0	1	1	6.376
Dino Gotchis	10.721	11.305	0	0	0	1	0	1	2.963
Doodles	11.311	13.229	0	21.254	1	1	1	1	7.008
Ethereans Official	0	8.591	6.064	18.057	0	0	0	1	1.221
Forgotten Runes	11.232	11.654	0	0	1	1	0	1	5.584
Fox Fam	9.025	9.928	6.935	16.440	0	1	1	1	2.954
Fugz	8.487	9.687	0	0	0	0	0	0	4.940
Invisible Friends	11.714	13.039	11.670	0	1	0	1	1	5.260
Kanpai Pandas	8.862	10.762	0	19.125	1	1	1	1	5.246
Lazy Lions	11.613	11.520	10.150	0	1	1	1	1	4.961
Lonely Aliens	0	10.174	8.349	0	0	1	1	1	2.908
Lucky Ducky	0	9.417	8.277	20.266	0	0	0	1	0.900
Lucky Sloths	7.618	8.435	6.757	19.779	0	0	1	1	1.221

Collection Name	*ln* (Discord Memb.)	*ln* (X Foll.)	*ln* (Instagram Foll.)	*ln* (GIPHY Views)	Ext. Valid.	Game Assets	Merch Integ.	Excl. Exp.	*ln* (Floor Price)
MeeBits	8.994	10.745	0	16.447	1	1	0	1	7.088
Memeland Potatoz	11.867	14.604	10.566	0	1	1	0	1	5.415
Milady Maker	9.681	9.480	0	0	1	1	1	1	8.147
Mocaverse	0	13.171	0	14.403	1	1	0	1	6.675
Moki Genesis	10.514	11.163	0	0	1	1	0	1	4.712
Moonbirds	9.460	12.394	0	0	1	1	1	1	8.370
Neiro Woofer Pack	0	11.136	0	0	1	0	0	1	3.704
Nouns	0	11.317	0	0	1	0	1	1	7.387
PhantaBear	0	10.886	9.198	0	1	1	1	1	3.789
Piggy Palz	0	6.743	0	0	0	0	0	0	2.275
Pudgy Penguins	12.040	13.473	14.509	24.976	1	1	1	1	9.409
Quirkies Original	10.697	10.972	0	0	0	1	1	0	7.392
Rexy	0	12.262	0	0	0	0	0	0	4.149
Robotos	0	10.867	8.487	0	1	1	0	1	2.990
Sappy Seals	9.882	11.507	0	22.004	1	1	1	1	5.868
Sproto Gremlins	0	9.434	0	0	0	0	0	0	6.157
The Dreamers	8.638	0	6.637	0	0	1	0	1	1.850
The Plushies	8.860	10.732	0	0	0	0	0	0	4.741
VeeFriends	0	12.419	12.405	22.391	1	0	1	1	8.184
World of Women	10.986	12.185	12.525	15.251	1	1	1	1	6.031

Note. These cell values represent the natural log-transformed data (*ln*) for the sampled NFT collections in the watchlist cohort. Binary variables (*Ext. Valid.*, *Game Assets*, *Merch Integ.*, *Excl. Exp.*) were not transformed; only discrete and continuous variables (*Discord Memb.*, *X foll.*, *Instagram foll.*, *GIPHY views*, *Floor Price*) were transformed using the formula $ln\ (x + 1)$, where x represents the corresponding, non-transformed (raw) cell data, in accordance with Brandes & Dölp (2025). All transformations are rounded to three decimal digits. The collections included in the watchlist cohort are organized in alphabetical order, not the order in which they were sampled. Abbreviations: *Memb.* = Members; *Foll.* = Followers; *Ext. Valid.* = External Validation; *Merch Integ.* = Merchandise Integration; *Excl. Exp.* = Exclusive Experiences/Features.