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"Dynamic Design of Overlapping NFT Auctions: From Theoretical Modeling to Market Simulation"

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Abstract

This study develops a dynamic model of NFT auction scheduling under overlapping conditions. By integrating bidder valuation theory, Poisson-based arrival processes, and inventory holding costs, we identify an optimal auction overlap rate that maximizes seller profit. Auction overlap creates a trade-off between maximizing bidder attention and minimizing time-based holding costs. Through simulation, we demonstrate that profit exhibits a concave relationship with overlap degree, confirming the existence of an interior optimum. Sensitivity analyses further reveal how holding costs influence the optimal auction spacing. Our findings offer practical guidelines for NFT sellers and platforms to design auction schedules that optimize profitability in attention-driven digital marketplaces.

Keywords: NFT Auctions; Overlapping Auctions; Dynamic Programming; Bidder Arrival Process; Auction Scheduling Optimization; Simulation Analysis

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1. Introduction

The Non-Fungible Token (NFT) market has rapidly emerged as a transformative segment within the broader digital economy, offering verifiable ownership of unique digital assets, including digital art, collectibles, music, gaming items, and virtual real estate. NFTs are underpinned by blockchain technology, which ensures transparency, immutability, and provable scarcity, and they have gained significant adoption through marketplaces such as OpenSea, Blur, Magic Eden, and Rarible. Following an extraordinary surge in popularity throughout 2021 - culminating in a peak monthly sales volume of over $5 billion - the NFT sector has since entered a more mature phase characterized by greater sophistication in auction design, market segmentation, and strategic seller behavior.

While the initial phase of NFT enthusiasm was largely driven by speculative investment and viral social media trends, the contemporary market now places increasing emphasis on auction mechanisms as tools for efficient price discovery and value maximization. Auctions have become particularly central for high-value NFTs, where intrinsic worth is subjective and depends heavily on factors like perceived scarcity, creator reputation, and community validation. However, as sellers adapt to this environment, they encounter new challenges concerning how best to structure and schedule multiple auctions to maximize visibility, maintain perceived asset exclusivity, and avoid cannibalizing demand.

One particularly pressing issue in this regard is the management of auction overlap - the scenario in which multiple NFT auctions are active at the same time or during overlapping time windows. While overlapping auctions can theoretically expand exposure and shorten inventory turnover periods, they also run the risk of fragmenting bidder attention and diluting competition across listings. In effect, too much overlap can erode final prices by making assets appear less unique or by overwhelming bidders' budgets, thus intensifying substitution effects.

Conversely, scheduling auctions too far apart may improve individual sale prices but extends the seller's inventory-holding period, thereby incurring additional holding costs and potential losses associated with market volatility and attention decay.

This paper systematically investigates the strategic trade-offs involved in overlapping NFT auctions by introducing a dynamic programming (DP) framework specifically tailored to auction scheduling optimization. We model a seller tasked with conducting ten NFT auctions, each of equal and flexible duration, within a total time window that can be compressed or stretched depending on the scheduling choices made. Bidder arrivals are modeled as a Poisson process, a standard method for capturing random arrival patterns in auction theory and queuing models. Critically, as multiple auctions overlap, the pool of arriving bidders is proportionally divided among all currently active auctions, a dynamic that reduces competition in each individual auction and, consequently, expected revenues.

The expected auction revenue is derived based on a functional form similar to that proposed by Pinker, Seidman, and Vakrat (2000), wherein auction outcomes deteriorate as bidder attention is divided among multiple simultaneous listings. Sellers, therefore, must find an optimal balance between auction duration, timing, and overlap, weighing the benefits of faster turnover against the risks of demand dilution. Our central objective is to compute an auction schedule - that is, a set of starting times for each auction - that maximizes the seller's total profit, defined as total revenue minus time-based holding costs.

Unlike prior studies, which have typically focused on auction format design (e.g., English vs. Dutch auctions) or bidder strategy analysis (e.g., sniping, entry deterrence), this study highlights temporal auction scheduling as an overlooked but crucial dimension of market design in NFT ecosystems. In attention-scarce environments - where buyer interest is influenced by hype cycles, influencer promotion, and broader media attention - the timing of an auction can be as critical as its format or reserve price. Sellers need to think not just about what they are auctioning, but when and how auctions are deployed relative to each other.

The contributions of this paper are threefold:

- First, we develop and implement a dynamic programming algorithm that computes profit-maximizing auction start times under varying levels of allowable overlap, thus providing a tool for sellers seeking to optimize scheduling under real-world constraints.
- Second, we validate the dynamic programming approach through a series of simulation experiments, systematically varying parameters such as bidder arrival rates, bidder valuation dispersion, and inventory holding cost coefficients to observe their impact on total revenue and auction completion time.
- Third, we conduct extensive sensitivity analyses to explore how the advantages and disadvantages of auction overlap change depending on market conditions. For example, in high bidder-intensity settings with low inventory costs, some degree of auction overlap may be optimal. Conversely, in thin or risk-averse markets, sequential auctions with minimal overlap could outperform simultaneous listings.

By integrating optimization modeling with behavioral insights about bidder attention and competition, this study offers actionable guidance for NFT sellers, auction platform designers, and researchers of digital marketplaces. In an economic landscape where attention is the ultimate scarce resource, understanding how auction timing affects seller profitability is critical to thriving in the increasingly competitive world of NFTs.

Ultimately, this paper aims to bridge the gap between auction theory and attention economics, offering a new perspective on how strategic auction scheduling - not merely asset quality or pricing - can substantially influence outcomes in decentralized, digitally mediated asset markets.

2. Online and Overlapping Auctions

With the rise of e-commerce platforms and real-time bidding environments, auction timing and scheduling have become central topics in auction design. Early contributions such as Bapna, Goes, and Gupta (2001, 2004) explored the dynamics of online auctions with continuous bidder inflow and heterogeneous user behavior. Bapna et al. (2007) were among the first to empirically study overlapping auctions, highlighting that concurrent listings often led to lower final prices due to bidder fragmentation and cognitive overload. Their later work (Bapna et al., 2009) provided a detailed characterization of bidder strategies in overlapping settings, identifying that "institutional bidders" often participate in multiple auctions simultaneously, altering the competitive landscape and price outcomes.

Pinker, Seidmann, and Vakrat (2000) developed one of the first analytical models capturing bidder dilution under multiple concurrent auctions, showing how the number of simultaneously active bidders significantly affects expected revenue. Their model incorporated variable bidder counts and uniformly distributed valuations, offering a closed-form solution to expected auction revenue under overlap. Shmueli, Russo, and Jank (2006) applied functional data analysis to online auction price trajectories and found temporal correlations between overlapping listings. Melnik and Alm (2005) also observed that overlapping auctions diminish seller reputation effects and suppress price realization, reinforcing the importance of temporal auction design. In a complementary study, Wang and Hu (2011) demonstrated that auction listing duration and timing significantly influence buyer arrival patterns, particularly in markets where attention is fragmented.

Chang (2012) extended these ideas by modeling overlapping auction markets using dynamic systems theory, demonstrating how bidders adjust entry timing and strategy across concurrent listings. His follow-up study (Chang, 2014) introduced an entropy-based measure to quantify strategic heterogeneity, with findings that overlap increases entropy in bidder behavior and reduces price predictability. In a related work, Jank and Shmueli (2010) examined intra-day auction scheduling, showing that buyer engagement fluctuates based on time-of-day effects, which can amplify the distortions caused by overlapping listings.

Zhuang and Popkowski Leszczyc (2022) developed a game-theoretic model of two overlapping auctions to identify optimal timing strategies. They showed that partially overlapping listings can yield higher revenue than fully sequential or fully simultaneous auctions, depending on bidder arrival rates and learning incentives. Their framework helps bridge the gap between theory and observed seller behavior in real-world markets. This was complemented by Liu and Park (2021), who used machine learning models to predict auction revenue based on scheduling inputs, confirming that overlapping structure is a key feature influencing final price variance.

Hendricks, Sorensen, and Wiseman (2024) offered a structural model of decentralized online markets with overlapping second-price auctions. Their findings revealed that even with high-frequency bidder arrivals, decentralized matching fails to achieve allocative efficiency. They also noted that market design interventions, such as centralized sealed bidding or dynamic posted prices, may improve overall outcomes. Similarly, Kauffman and Wang (2020) emphasized the importance of platform-level design in mitigating the inefficiencies caused by overlapping listings.

Greve (2023) explored overlapping auction behavior in high-end art and NFT markets, documenting strategic date alignment by major auction houses such as Christie's and Sotheby's. His analysis demonstrated that firms often prefer being the second auction to benefit from price signals revealed in the first, leading to equilibrium overlap even when spacing might be more efficient. He developed a two-period strategic game model showing how auction houses anticipate each other's scheduling and strategically position themselves.

Recent NFT market research (Bourron, 2023) analyzed the transition from hype-driven drops to stabilized auction schedules. Observations included herding behavior in early NFT sales and growing strategic awareness of auction timing among both sellers and bidders. These findings suggest that even in speculative or decentralized environments, overlap decisions substantially impact bidder attention and final outcomes. Moreover, Cong, He, and Tang (2022) showed that timing in NFT auctions significantly influences valuation, especially when paired with social signals such as likes and retweets. Takahashi and Yamamoto (2023) provided further support by analyzing how narrative context and exclusivity cues - often tied to drop timing - affect perceived value.

3. Modeling the Impact of Auction Overlap in NFT Markets

To rigorously examine how auction overlap influences outcomes in NFT marketplaces, we develop a comprehensive and dynamic mathematical model rooted in bidder behavior theory and real-world auction scheduling patterns. Our modeling approach aims to capture the intricate mechanisms by which overlapping auctions dilute bidder attention, redistribute bidder arrival intensity, and ultimately influence auction revenue generation and seller profitability. Building upon empirical insights from NFT markets and foundational auction theory, we introduce a framework that treats auction scheduling and overlap not merely as static choices but as active levers that can dramatically alter auction outcomes. This model serves as the foundation for subsequent simulation studies and sensitivity analyses, providing a systematic means to explore optimal auction design under varying market and behavioral conditions.

3.1. Bidder Valuation Framework

We assume a market consisting of bidders, where each bidder's valuation for a given NFT is independently and identically distributed (*i.i.d.*) according to a uniform distribution over the interval $[\mu - s, \mu + s]$, where:

- μ denotes the mean willingness to pay.
- s denotes the dispersion (spread) of valuations.

Following Pinker, Seidmann, and Vakrat (2000), the expected winning price in a standard English auction with bidders is derived as:

$$P(n) = \mu + s - \frac{4s}{n+1}$$

This relationship highlights that while a higher number of bidders, n generally increases expected prices, the marginal benefit diminishes as n grows.

3.2. Auction Duration and Bidder Arrival Dynamics

Each auction is designed to last for a fixed duration d. Bidders arrive according to a Poisson process with an average arrival intensity λ. However, because multiple auctions may overlap temporally, the effective arrival rate per auction depends on the number of concurrently active auctions.

Let $r \in [0,1]$ represent the overlap or spacing ratio or the proportion of overlap between successive auctions. If $r = 0.5$, each auction starts halfway through the duration of the preceding auction. Thus, the start time of the auction i is:

$$t_i = (i-1) \cdot r \cdot d$$

The total auctioning time horizon is given by:

$$T = (k-1) \cdot r \cdot d + d = \big((k-1) \cdot r + 1\big) \cdot d$$

where k denotes the number of auctions.

We formulate the profit maximization problem as dynamic programing over the overlap parameter r. Bidder arrival Process is characterized as follows. Let $A(t)$ be the number of active auctions at time index t then then the arrival rate per auction at time t is

$$\lambda_i(t) = \frac{\lambda}{A(t)}$$

The expected bidder count for auction *i is*

$$n_i(r) = \int_{t_i}^{t_i+d} \frac{\lambda}{A(t)}\, dt$$

Then the individual auction Revenues and the total market revenue can be calculated using the following functions.

$$R_i(x) = \mu + s - \frac{4s}{n_i(r)+1}$$

and the total market revenue is

$$R(x) = \sum_{i=1}^{k} R_i(r)$$

In the inventory holding cost calculation, we apply the following cost Functions.

$$C_H(r) = h \cdot T(r) + C$$

where h denotes the holding cost coefficient and C is the fixed overhead component.

The objective is to maximize the total profit.

$$V(r) = R(r) - C_H(r)$$

The dynamic programming objective becomes:

$$r^* = \arg\max_{r \in [0,1]} V(r)$$

This can be solved numerically by discretizing r over a grid and evaluating the profit function $V(r)$ using numerical integration or time-discretized simulation.

4. Simulation Study and Sensitivity Analysis

4.1. Simulation Setup

To operationalize the model, we simulate the scheduling and outcome of $k = 10$ NFT auctions under varying levels of overlap r. For each r in a finely discretized range , the simulation executes the following steps:

1. Auction Scheduling:
   Compute auction start times t_i using r.
2. Timeline construction:
   For each small time interval Δt, count active auctions $A(t)$.
3. Bidder distribution:
   Divide arriving bidders equally among active auctions at each t.
4. Revenue estimation:
   Integrate expected bidder arrivals over each auctions' timeline to calculate $n_i(r)$ and $R_i(r)$
5. Cost computation:
   Evaluate holding costs $C_H(r)$
6. Profit calculation:
   Compute $V(r) = R(r) - C_H(r)$

We then identify r^* that maximizes V(r). Additionally, we conduct a sensitivity analysis across various holding cost rates h, recording the corresponding optimal overlap $r^*(h)$ for each case. Results are tabulated, and trade-offs between overlap, duration, and profitability are visualized.

4.2. Overlap & Pairwise Overlap Proportion: Illustrative Cases

To clarify the concept of "spacing or overlap" r and how it relates to pairwise overlap proportion observed in scheduling, consider the following examples:

- Two-Auction Case: Suppose we schedule Auction 1 at time 0 and Auction 2 at time $r \cdot d$. The auctions overlap for a duration of $(1-r) \cdot d$. Since only one pair exists, the pairwise overlap proportion equals the normalized overlap duration, which is 1−r.
- Three-Auction Case: We consider the three possible pairs: (1,2), (1,3), and (2,3). Suppose each auction starts at $t_1 = 0$, $t_2 = r \cdot d$, and $t_3 = 2 \cdot r \cdot d$. If $r = 0.5$, then:
  - Auction 1 and 2 overlap between $t = 0.5 \cdot d$ and $t = d$
  - Auction 2 and 3 overlap between $t = 1.0 \cdot d$ and $t = 1.5 \cdot d$
  - Auction 1 and 3 do not overlap → Total of 2 overlapping pairs out of 3: pairwise overlap proportion = 66.7%

In general, the overlap rate r is the designer's input to determine auction spacing, while the pairwise overlap proportion is computed ex post by counting overlapping pairs. They often align closely when spacing is regular and evenly distributed.

4.3. Simulation Logic (Pseudocode Overview)

Rather than presenting full implementation code, we summarize the logic as pseudocode and key computational steps. This abstraction preserves clarity while maintaining the core structure of the implemented algorithm. (Full code is available upon request).

Pseudocode for Overlap-Profit Simulation:

```
for each holding cost rate h in range(0, 1.0):
  for each overlap r in [0, 1]:
    initialize time window T based on r
    initialize empty list of auction start times
    for i in 1 to num_auctions:
      find time t that maximizes expected profit
      append t to list of start times
    compute revenue from expected bidder counts using overlapping density
    compute total cost using h and T
    record total profit = revenue – cost
```

The simulation results reveal several key findings. Total profit exhibits a concave relationship with respect to *r*, confirming the existence of an interior optimum *r**. Sequential auctions (low r) maximize revenue but incur higher holding costs; highly overlapped auctions (high r) minimize costs but dilute revenues. As holding cost rate increases, the optimal overlap shifts towards higher values, favoring faster liquidation. The relationship between r and pairwise overlap proportion is nonlinear, especially with more auctions, necessitating careful scheduling design.

Figures 1 through 3 visually depict these dynamics, showcasing how total profit varies with and how holding cost sensitivities impact optimal auction scheduling. Results are then visualized in 2D and 3D plots to analyze the relationship between overlap, holding cost, and profit.

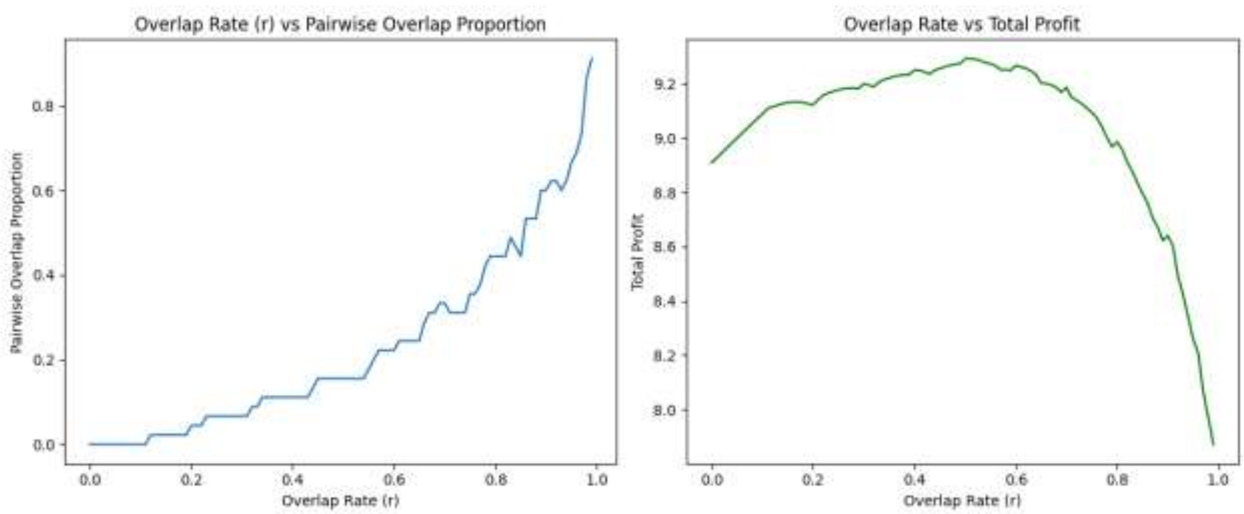

Figure 1 and Figure 2

Figure 1 shows the relationship between overlap rate r and pairwise overlap proportion. This figure illustrates how the pairwise overlap proportion increases as the overlap rate *r* rises from 0 (fully sequential auctions) to 1 (fully simultaneous auctions). Although the relationship is approximately linear for small numbers of auctions, it becomes increasingly nonlinear as the number of auctions grows, reflecting the complex combinatorial dynamics of auction scheduling. Figure 2 is about the total profit as a function of overlap rate *r*. This figure depicts the concave relationship between the total profit and the auction overlap rate. An interior maximum exists, indicating the optimal level of overlap that balances the revenue benefits of bidder concentration with the cost savings from shorter inventory holding durations. Overlapping too little or too much both lead to suboptimal profits.

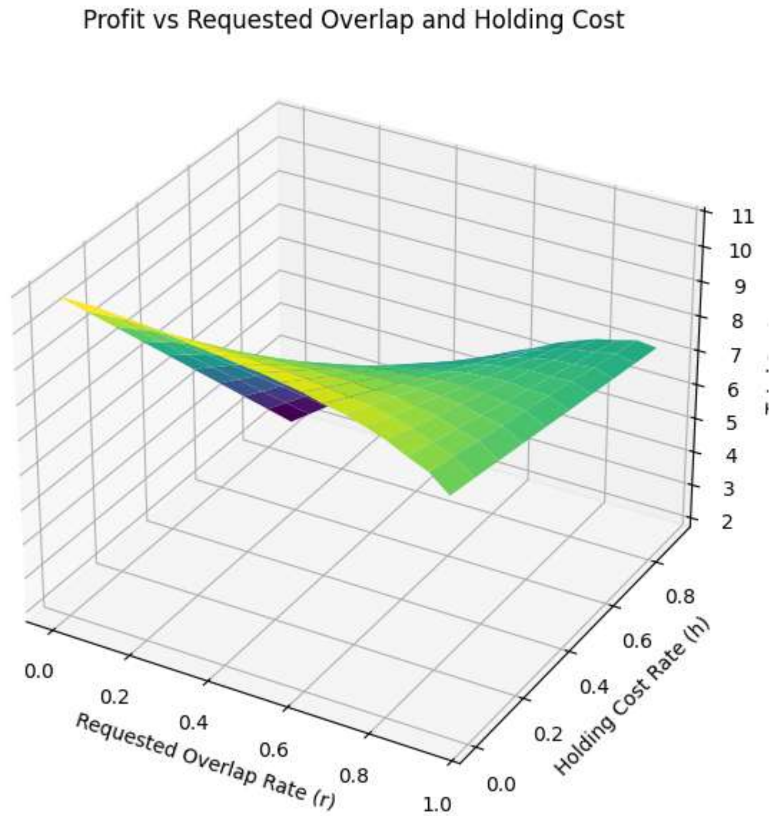

Figure 3

Figure 3 is about the sensitivity of optimal overlap $r*$ to holding cost rate h. This figure shows how the optimal overlap rate $r*$ increases as the marginal inventory holding cost rate h rises. When holding costs are low, sequential auctions (lower $r*$) are preferred to maximize revenue per item. As holding costs increase, sellers are incentivized to overlap auctions more heavily to expedite inventory liquidation and minimize time-related expenses.

5. Discussion

Our results demonstrate that auction overlap introduces a nuanced trade-off between speed and profitability. Sequential auctions (low overlap) benefit from concentrated bidder attention and high revenue per auction, but they incur longer total durations and higher holding costs. In contrast, heavily overlapped auctions reduce duration and costs but dilute demand across simultaneous sales, leading to lower revenue per item.

The simulations reveal the existence of an interior optimal overlap level that balances these effects. This optimum shifts depending on the holding cost rate . When it is low, sellers can afford to space auctions more widely to extract higher prices. As increases, overlapping becomes more favorable to minimize cost exposure.

Interestingly, the relationship between overlap rate and pairwise overlap proportion is nonlinear, especially for larger numbers of auctions. This discrepancy suggests that auction designers must consider not only the intended overlap but also how scheduling logistics affect cumulative exposure.

Our model highlights the importance of accounting for dynamic bidder allocation. By treating arrival rates as distributed across active auctions, we capture the competitive tension introduced by overlap and model attention dilution as an endogenous feature rather than an external shock.

6. Conclusion

This paper has developed a dynamic framework for auction scheduling in NFT markets under conditions of potential auction overlap, addressing a critical operational challenge in attention-scarce digital environments. By systematically integrating bidder valuation models, dynamic bidder arrival processes, auction overlap mechanics, and inventory holding cost considerations, we offer a unified optimization strategy for determining profit-maximizing auction timing.

A central contribution of this study is the identification of an interior optimal overlap rate. Rather than treating overlap as universally advantageous or detrimental, our analysis reveals that the profitability effects of auction overlap are contingent upon a delicate balance between several forces: the dilution of bidder attention across simultaneous auctions, the redistribution of arriving bidders among active listings, and the time-sensitive costs associated with inventory management. This nuanced relationship underscores the complexity of scheduling decisions in digital marketplaces where bidder psychology, attention scarcity, and platform dynamics interact in nontrivial ways.

Through rigorous simulation analysis, we validate the theoretical predictions of the model and demonstrate how auction designers can operationalize the insights. The simulations show that as the inventory holding cost rate increases, sellers have a stronger incentive to overlap auctions more aggressively to minimize cost exposure. Conversely, when holding costs are low, spreading auctions sequentially becomes advantageous to maximize revenue per auction. The resulting profit function exhibits clear concavity with respect to the overlap parameter, ensuring the existence and uniqueness of an interior optimum. Moreover, the simulation results confirm that even modest misalignments from the optimal overlap level can lead to significant reductions in total profit, highlighting the importance of precise timing decisions.

The implications of these findings are substantial for NFT sellers, platform operators, and market designers. Sellers should recognize that neither extreme sequential scheduling nor full simultaneous launches will necessarily maximize outcomes. Instead, auction timing should be dynamically adapted to prevailing market conditions, bidder arrival intensities, and platform holding cost structures. NFT marketplaces could further enhance seller outcomes by providing analytical scheduling tools or predictive bidder flow models that account for expected competition and bidder overlap.

Importantly, this research also bridges a gap in the existing auction theory literature by extending attention-based models to explicitly incorporate time-based overlap dynamics in decentralized, digital-first auction environments. While prior studies have explored auction formats, reserve prices, and bidder entry behavior, few have directly tackled the issue of temporal auction spacing as a strategic design variable - particularly in blockchain-enabled markets characterized by high volatility and rapid information propagation.

Future research avenues are rich and promising. Extensions could incorporate more complex bidder behavior, such as strategic learning, sniping tactics, or cross-auction budget constraints. In addition, modeling multi-platform dynamics, where bidders simultaneously monitor auctions across OpenSea, Blur, and other NFT marketplaces, would further enrich the practical applicability of the framework. Incorporating the impact of social amplification effects - such as viral promotions, influencer endorsements, or community-driven hype cycles - could also yield deeper insights into how external signals interact with optimal scheduling strategies. Finally, adaptive auction designs, where sellers update auction start times in real time based on observed bidder traffic, represent an exciting direction for future theoretical and empirical exploration.

In conclusion, this study provides a robust theoretical and practical foundation for optimizing NFT auction schedules under overlapping conditions. By embracing a dynamic, data-driven approach to auction design, sellers and platforms can more effectively navigate the complexities of the digital asset economy, maximizing profitability while sustaining bidder engagement in an increasingly competitive and fragmented attention landscape.

References

Bapna, R., Goes, P., & Gupta, A. (2001). Insights and analyses of online auctions. Communications of the ACM, 44(11), 42–50.

Bapna, R., Goes, P., & Gupta, A. (2004). User heterogeneity and its impact on electronic auction market design: An empirical exploration. MIS Quarterly, 28(1), 21–43.

Bapna, R., Chang, S. A., Goes, P. B., & Gupta, A. (2007). Overlapping online auctions: Empirical characterization of bidder strategies and auction prices. MIS Quarterly, 31(1), 1–23.

Bapna, R., Chang, S. A., Goes, P. B., & Gupta, A. (2009). Overlapping online auctions: Empirical characterization of bidder strategies and auction prices. MIS Quarterly, 33(4), 763–783.

Bourron, C. (2023). Comprehensive analysis of the trade of NFTs at major auction houses: From hype to reality. Arts, 12(5), 212. https://doi.org/10.3390/arts12050212

Chang, S. A. (2012). Time dynamics of overlapping e-auction mechanisms: Information transfer, strategic user behavior and auction revenue. Information Systems Frontiers, 14(2), 331–342.

Chang, S. A. (2014). Multiple overlapping online auction market: Bidder strategic mixture analysis using entropy. Decision Support Systems, 64, 57–66.

Cong, L. W., He, Z., & Tang, K. (2022). Crypto, NFTs, and the valuation of digital scarcity. Review of Financial Studies, 35(8), 3883–3924.

Greve, T. (2023). Overlapping auctions. SSRN Working Paper No. 4672348. https://ssrn.com/abstract=4672348

Hendricks, K., Sorensen, A., & Wiseman, T. (2024). Dynamics and efficiency in decentralized online auction markets. Working paper, University of Wisconsin–Madison.

Jank, W., & Shmueli, G. (2010). Modeling the dynamics of online auctions: A modern statistical approach. Wiley Series in Probability and Statistics.

Kauffman, R. J., & Wang, B. (2020). Bidder behavior and seller strategies in overlapping online auctions: A systems design perspective. Electronic Commerce Research and Applications, 42, 100993.

Liu, Q., & Park, Y. (2021). Predicting auction success using temporal and structural features of online listings. Journal of Retailing and Consumer Services, 61, 102543.

Melnik, M. I., & Alm, J. (2005). Buyer and seller reputation on eBay: The value of trust. Journal of Industrial Economics, 53(1), 85–105.

Pinker, E. J., Seidmann, A., & Vakrat, Y. (2000). Managing online auctions: Current business and research issues. Management Science, 49(11), 1457–1484.

Shmueli, G., Russo, R. P., & Jank, W. (2006). Modeling auction price dynamics using functional data analysis. Journal of Business & Economic Statistics, 24(4), 470–481.

Takahashi, M., & Yamamoto, H. (2023). Narrative value and scarcity in digital art auctions. Journal of Cultural Economics, 47(2), 213–240.

Wang, X., & Hu, Y. (2011). The effect of timing and duration on online auction performance. Electronic Commerce Research, 11(1), 43–67.

Zhuang, H., & Popkowski Leszczyc, P. T. L. (2022). Optimal seller strategy in overlapping auctions. Journal of Retailing and Consumer Services, 65, 102883.