Competitive Arousal, Temporal Clustering, and Overbidding Dynamics in an Auction Platform

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Abstract **— Auctions provide a unique lens through which to study human behavior and decision-making in competitive environments. These scenarios involve complex dynamics and strategic choices, where interactions between bidders lead to financial outcomes. During auctions, individuals must make quick decisions under pressure while navigating conditions such as item scarcity, information asymmetry, and emotional arousal. By examining bid increments and participant engagement across different auction formats, researchers can gain valuable insights into decision-making processes in competitive settings. This paper presents the findings of a preliminary study that analyzed a dataset from a popular online auction platform where users bid on various types of retail products. The study focused on three key aspects: competitive arousal, temporal clustering, and overbidding. The results reveal that nearly half of the bids occur near the closing time due to competitive arousal, and user activity peaks in the evening. However, contrary to expectations, such temporal clustering does not result in higher average item prices. Furthermore, the dataset revealed instances of overbidding, suggesting the presence of irrational behavior that requires further investigation.**

Keywords – auctions; big data analytics; human behavior.

I. INTRODUCTION

Auctions are a popular method of selling items where the highest bid determines the price paid by the buyer. They are generally classified as vertical or horizontal based on the type of items being sold. The former type focuses on a specific category (e.g., artwork), whereas horizontal auctions encompass a broader range of categories, catering to either consumer or business products, depending on their target audience. Online auctions have gained increasing popularity since the introduction of the first Internet marketplace in 1995. Specifically, in the past decade, the online auction industry has experienced significant growth and transformation due to several factors, including advancements in technology, the introduction of digital products and non-fungible tokens (NFTs), changing consumer demographics and behaviors, the increasing online auctioning of surplus, and external circumstances such as the COVID-19 pandemic. This growth is projected to continue in the future at a compound annual growth rate (CAGR) of 12.36%. In 2028, the online auction market is expected to expand by 3,076.64 million US dollars [1].

Two distinct categories of online auction websites have emerged in the past decades: traditional platforms and marketplaces. The former category adopts a centralized approach, i.e., the website organizes auctions that typically encompass a collection of items, and users retain the ability to bid on an individual item basis. Examples of this model are Christie's and Sotheby's, two vertical auction websites that sell artworks. In this case, the auction house is usually responsible for selling and delivering products. On the contrary, two-sided marketplaces facilitate matchmaking between sellers and buyers. A prominent example is eBay, where users can initiate and manage their own auctions, each usually involving individual items or collections across various categories of goods. In marketplaces (e.g., eBay), the seller is directly responsible for shipping the items to the buyer. Online auctions can be either timed, where bids are accepted until a fixed deadline, or real-time, mimicking the immediate, competitive nature of live auctions. Moreover, they can incorporate novel features, such as eBay's popular "buy it now" button (i.e., buy price auctions [2]), which enables a buyer to skip incremental bids and directly agree to a final price set by the seller.

Auctions provide a unique lens through which human behavior can be studied, particularly in the realms of decision-making, strategy, and economic interaction [3]. The data generated in auction environments, characterized by competitive bidding, time constraints, and varying levels of information asymmetry, offer rich insights into how individuals make decisions under pressure, uncertainty, and scarcity [4]. Behavioral economists have long been intrigued by how bidders assess value, manage risk, and react to the actions of competitors [5]. For instance, auction data can reveal patterns of irrational bidding, such as the "winner's curse" [6], where winners tend to overpay due to competition. Researchers can gain a deeper understanding of cognitive biases and strategic decision-making in competitive environments by analyzing bid increments, winning bids, and participant behavior across various auction types [7]. Nowadays, the application of machine learning and advanced statistical techniques to auction data has opened new avenues for understanding human behavior. For instance, analyzing bidding patterns can help identify when a bidder is likely to drop out of an auction or if a bid is successful [8][9]. These insights are invaluable in economic theory and practical applications like designing more efficient auction systems, tailoring marketing strategies to consumer behavior, or providing bidders with tools for more informed decisions.

This paper presents the results of a study that investigated a popular retail auction website. Our research focused on three auction and human dynamics: competitive arousal, temporal clustering, and overbidding, usually studied in simulations or auction marketplaces (i.e., eBay).

II. RELATED WORK

Auction behavior and the analysis of bidding dynamics have received increased attention since the introduction of online auction websites. The authors of [10] studied fixed-end auctions and discovered that seasoned bidders tend to employ more opportunistic strategies, e.g., placing a winning bid at the last possible moment (i.e., sniping). As a deterrent, several auction websites implement a soft close, i.e., a mechanism that extends the end time for a specific item if a bid is placed in the last minutes of the auction [11]. However, several articles found that enabling bidders to extend the auction time by submitting their bids in the closing minutes or seconds leads to large price increases at the end of the auction [11] [12] [13]. In peer-to-peer auction sites, vendors exploit this dynamic to artificially increase an item's price or desirability using friend or false accounts submitting bids (i.e., shill bidding) [14]. In business-to-consumer auction platforms, end-of-auction notifications and reminders influence user behavior and success rates in last-minute bidding [15]. As a result, platforms such as eBay have specific policies to prevent it. The study by [16] showed a more nuanced user categorization based on their arrival time in an auction. Specifically, the authors define three groups: evaluators, opportunists, and participators. Individuals in the former category place their bids early in the auction and then evaluate their decisions based on the next events; late bidders are considered opportunists because they often exploit last-minute chances; the latter category involves individuals who place multiple bids throughout the auction. The work by [17] confirmed that more seasoned bidders are typically the last to bid in eBay auctions, while novice bidders and evaluators are often the first. Other studies found that bidder experience has a nonmonotonic impact on the timing of bids. As a result, experienced bidders are more active at the beginning or toward the end of auctions and tend to engage less in multiple bidding [18].

Other research on factors such as information and temporal clustering studied the role and impact of the alternatives available to bidders in auctions that extend over multiple days. The authors of [19] compared the cost of bidding and searching for information, including price alternatives, throughout the lifetime of an auction. Specifically, they investigated the equilibrium achieved by early bidding when users can search and access the items elsewhere, whether inside the online auction website or externally. Although temporal clustering represents an interesting aspect, there is a lack of information on bidders' activity and engagement throughout the day. Apparently, the auctioning and the bidding stakeholders might have opposite interests. Specifically, it would be in the seller's (or auction website's) interest to end the auction when there is a peak of user engagement, whereas bidders might find less competition in days and times with less activity. Several posts on online communities and forums discuss strategic days and times to end an eBay auction to achieve the most visibility, engagement, and, consequently, a more favorable price. However, there is little research and scientific evidence on temporal clustering aspects. Finally, studies focusing on aspects of interest for behavioral economics uncovered that bidders often exhibit irrational behaviors that deviate from the predictions of traditional economic models [5]. For instance, research has highlighted the presence of overbidding, where participants bid beyond the item's intrinsic value [6]. This dynamic is often attributed to the winner's curse, which suggests that the winner of an auction tends to overestimate the item's value due to emotional engagement, competitive arousal, or other factors such as auction format. For instance, the winner's curse often happens in blind auctions, where bidders are unaware of the item being auctioned. This is the case of bulk auctions (where multiple items are being sold together) or auctions involving sensitive or unique items (where maintaining confidentiality is important). Also, the winner's course happens in sealed-bid auctions, where the values of bids are not disclosed until the end to prevent bidders from being influenced by others, thus promoting a fair and competitive auction process. Nevertheless, research studies also found overbidding in auctions that are completely transparent with respect to information such as the item's actual price, bid history and value, and number of users interested in the item. These findings suggest that auctions trigger a form of competition that can evoke strong emotional responses, leading to decision-making that prioritizes winning over economic rationality [6].

III. MODEL OF THE AUCTION WEBSITE

Our study focuses on a popular horizontal auction website operating in the United States and targeting the consumer space with a centralized approach based on physical warehouse locations distributed across several states. The name of the platform and the specific locations of the warehouses where the auctions are held will remain undisclosed to uphold the confidentiality of both the auction house and its users. Furthermore, specific data not crucial for our study, including descriptive and inferential statistics about the dataset, are represented in an approximated form to avoid disclosing significant information about the business. The website involves a digital and physical sales approach based on a network of company-owned warehouses, which serve as the locations for the items auctioned. Every day, the website lists multiple auctions in each of the locations. Each auction consists of a different number of items, which users can bid on individually. As a result, each item can be considered a separate auction. Although, in several cases, the items in an auction belong to the same category, auctions usually include various products across various categories, such as clothing, toys, tools, books, technology, food, and occasionally, industrial equipment, vehicles, and bulk items. Once auctions are published on the website, users usually have between 3 to 10 days to review the items and place their bids. Although each auction has a set end date that applies to all its items, any bids placed on an item near the expiration time extend the end date of bidding on that item by several minutes, allowing other users the chance to submit higher bids (i.e., soft close). The minimum bid for each item auctioned begins at a nominal starting price of $0.01, with increments proportionally ranging from $0.05 to $100 depending on the current bid amount range. For instance, the minimum increment for an item priced between $1 and $10 is $1, but it increases to $2.5 for items priced $10-$20. Users can place incremental bids or specify a maximum amount to outbid any bids lower than the amount. The winner is charged at the end of the auction when taxes and fees are added.

A distinctive aspect of this platform is the requirement for buyers to physically collect their won items from the respective warehouse locations on specific dates. This differs from other centralized online auctions, where items are usually shipped to buyers. In fact, upon collection, users are afforded the opportunity to inspect the item's quality, check for the presence of damage, identify potentially missing pieces, and verify their operational status. This is because all items sold by the platform are new, though many are end-of-line, remaining stock, refurbished, expired, or returned items. Therefore, the company's refund policy categorizes them into two main groups: those eligible for a refund in case of damage, malfunction, or misrepresentation discovered at pick-up and those not eligible for refunds. This information is highlighted in the item description. Refunded items are re-listed as non-refundable until eventually bought. Items not collected by the winner are also re-listed.

IV. Preliminary Dataset Analysis

The dataset utilized in this study consists of secondary data from 310,000 auctions held in more than 320 locations between 2018 and 2023. During this period, 25 million items were auctioned on the website, resulting in over 400 million USD in revenues. Over 7.5 million unique items were listed for auction in the past year. They received over 193 million bids from more than 220,000 unique users. The auction website has expanded its operations since its launch in 2018. Its warehouse locations doubled in number in the first two years, reaching a peak of over 110 locations in 2021 and, subsequently, decreasing to approximately 100 locations from 2022 onwards. Figure 1 shows the steady growth in monthly active warehouses. Following this trend, the dataset reports an increase in the number of auctions held and items sold. Specifically, the data show more than a three-fold increase in the number of auctions (i.e., from approximately 30,000 to 100,000) and slightly less than three-fold increase in the number of items sold (i.e., from 2.5 to 8 million), in the period from 2019 to 2023. Also, the website has grown significantly from a revenue standpoint, from \$10 to over \$100 million from 2018 to 2023. Although aspects strictly related to finances are beyond the purpose of this paper, the growth during the COVID-19 pandemic is noteworthy. The nature of the dataset (i.e., secondary data) prevents us from conducting experimental studies on users. Nevertheless, the dataset's size and real-world nature enable us to study and gain insight into actual auction behavior and dynamics such as competitive arousal, temporal clustering, and irrational behavior, which are usually explored only in simulations, small-scale experiments, or marketplaces (e.g., eBay).

A. Competitive arousal

Competitive arousal in auctions refers to the heightened emotional state and desire to win that bidders experience when competing against others. We initially focused on competitive arousal to confirm that the platform's operation can be modeled as an auction platform based on the expected user behavior. In auction platforms, one typical manifestation of competitive arousal is an increase in bids toward the end of auctions. Such bids are placed by users participating in the auction since the initial and intermediate phases (i.e., evaluators and participators) or by opportunists (i.e., snipers) [16] [17] [18].

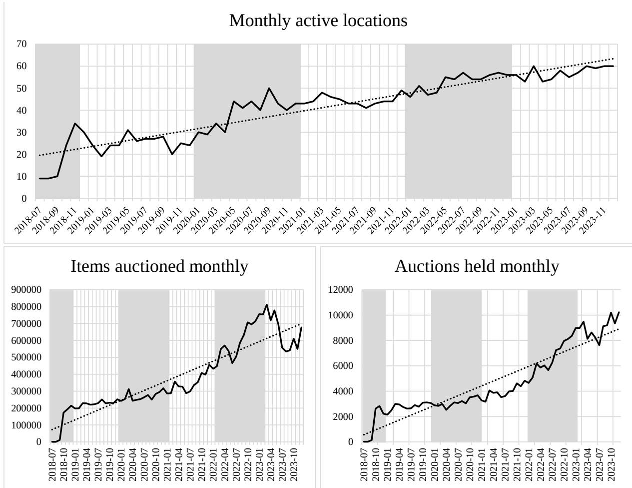

Figure 1. Growth of the auction house from 2018 to 2023.

Our analysis confirms the presence of competitive arousal, as the dataset shows a distinct pattern in bidding behavior, characterized by a gradual intensification toward the auction's conclusion in most cases. Specifically, data shows that only 13.57% of bids occur at the beginning, with 38.03% in the middle and a significant 48.39% towards the closing time. Our findings are consistent with other studies in the literature, including research on herd behavior [12] [13].

In addition, the dataset exhibits bursts of last-minute bids from users who join the auction right before its closing (i.e., snipers). This might be due to the fact that the website enables users to add items to a watchlist and activate push notifications 10 minutes before the auction end. Auction-end reminders might help drive additional traffic, stimulate competition, and drive prices up independently of competitive arousal. There could be several explanations for these findings. For instance, most experienced bidders might prefer adding items to the watchlist instead of placing early bids. This enables them to evaluate other bidders' behavior in the initial and intermediate stages without sharing any information about their interest in the item or perceived value and, most importantly, without influencing the auction. By doing this, they can gather information about the number of bidders and item value and intervene toward the end if still interested in the item. This is consistent with previous studies [19] that analyzed the value and cost of information in auctions: adding the item to their watchlists has an inferior cognitive cost than placing a bid (i.e., does not require users to make decisions about bid value) and, simultaneously, it enables users to gather information without the risk of increasing the item's price. Furthermore, although the auction website implements soft-closing mechanisms that extend the auction duration for every bid placed near the end, bidders could still attempt sniping. For instance, users might think that auctions ending at specific times of the day may receive less engagement or result in an opportunity to overbid other users when they are busy with other tasks. Although the dataset does not contain whether bidders activated end-of-auction notifications or watchlists, one hypothesis to be tested in a follow-up study is that the consistent sniping behavior of experienced bidders involves the use of tools, whether internal (i.e., watchlist) or external (e.g., timer), to visit an auction before its end.

Also, the data show that less than 10% of bidders who join early remain engaged until the end, in accordance with previous literature [16]. This might suggest that either they are novice users or experienced bidders who use other known strategies (e.g., bid shielding, that is, placing a high enough bid to discourage others), to maintain a winning position until the ending phase. We will explore this dynamic in a follow-up study, where we will focus on profiling users and inferring their experience.

In addition to confirming that our dataset behaves according to an auction model, the analysis of competitive arousal was particularly crucial, given the preliminary stage of our research project, to identify item categories, brands, and even specific products that are especially sought after and, consequently, to guide our future research. This is especially true considering that the auction platform sells a wide array of generalist products. In fact, while our data shows that the average bid count per item is 20 with a degree of competitive arousal similar to other platforms (i.e., 50% of bids in the second half of the auction), about 5 million items (i.e., 20% of the total) present different levels of heightened competitive arousal, of which approximately 360,000 items (i.e., 0.14%) received more than 50 bids, mostly in the last quartile of the auction. Among these items, almost 1400 received more than 100 bids, mostly skewed toward the end of the auction. Finally, 45 items (i.e., furniture and home accessories) had more than 150 bids and experienced extremely high levels of competitive arousal.

B. *Temporal clustering*

As competitive arousal dynamics result in increased bidding toward the end of the auction (i.e., approximately 50% of bids are placed at the end of the auction), two reasonable hypotheses would be that (1) the day and time when an auction ends results in different levels of competition due to users' daily activities, and (2) increased competition would lead to an average higher item price. Therefore, our second analysis focused on users' bidding activity throughout the day. To this end, we evaluated the hourly and weekly distribution of bids based on the end day and time of auctions. Among the bids placed in 2023 (i.e., approximately 165 million), most of them (i.e., 99.09%) were realized at 18 warehouse locations, which are the ones taken into consideration for the purpose of this study.

Although auctions are set to end every 30 minutes throughout most of the day (i.e., from 7 AM to 11 PM), the data (see Figure 2) clearly show a distinct pattern of user activity, with lower engagement between 11 PM and 7 PM (users can still bid even if auctions do not close during this period) and increased activity from 7 AM to 4 PM, with the highest engagement from 5 PM to 9 PM when competition for auction items appears fiercest. Indeed, this aligns with typical life and workday patterns, where bidders might be more active outside of regular working hours. This observation could be aligned with theories suggesting that individuals participate more actively during leisure or non-working hours, indicating a temporal preference for engagement in auction activities. The data confirm our first hypothesis, showing a statistically significant reduction in bidding between 11 AM and 4 PM on Tuesday, Wednesday, Thursday, and Friday. Although this result is trivial, it is key for addressing our second hypothesis.

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
00	2%	2%	2%	2%	2%	2%	2%
01	1%	1%	1%	1%	1%	1%	1%
02	1%	1%	1%	1%	1%	1%	1%
03	1%	1%	1%	1%	1%	1%	1%
04	1%	1%	1%	1%	1%	1%	1%
05	2%	2%	2%	2%	2%	2%	1%
06	3%	3%	3%	3%	3%	3%	2%
07	4%	4%	4%	4%	4%	5%	4%
08	5%	5%	5%	5%	5%	5%	5%
09	5%	5%	5%	5%	5%	5%	5%
10	5%	5%	5%	5%	5%	5%	5%
11	5%	4%	4%	4%	4%	4%	5%
12	5%	4%	4%	4%	4%	4%	5%
13	5%	4%	4%	4%	4%	5%	5%
14	5%	4%	4%	4%	4%	5%	5%
15	5%	4%	4%	4%	4%	4%	5%
16	5%	5%	5%	4%	4%	5%	5%
17	6%	6%	6%	6%	6%	6%	6%
18	7%	8%	7%	7%	7%	7%	6%
19	9%	9%	8%	8%	9%	8%	8%
20	9%	9%	9%	9%	9%	8%	8%
21	7%	7%	7%	7%	7%	7%	7%
22	4%	4%	4%	4%	4%	5%	4%
23	3%	2%	3%	3%	3%	3%	3%

Figure 2. Temporal clustering: percentage of daily user activity by hour.

Average price (compared to MSRP)							
	Mon	Tue	Wed	Thu	Fri	Sat	Sun
07	11%	13%	11%	14%	14%	6%	6%
08	12%	13%	12%	12%	12%	12%	12%
09	12%	13%	12%	13%	13%	11%	11%
10	12%	13%	12%	12%	12%	12%	12%
11	12%	12%	12%	11%	11%	12%	12%
12	11%	11%	11%	12%	12%	14%	14%
13	12%	12%	11%	12%	12%	13%	13%
14	13%	12%	12%	12%	12%	12%	12%
15	12%	14%	12%	11%	11%	12%	12%
16	12%	13%	11%	12%	12%	12%	12%
17	13%	12%	12%	14%	14%	12%	12%
18	13%	13%	13%	13%	13%	12%	12%
19	11%	13%	12%	12%	12%	12%	12%
20	12%	13%	12%	11%	12%	13%	12%
21	13%	12%	13%	13%	14%	12%	12%
22	9%	10%	15%	11%	13%	11%	14%
23	12%	10%	9%	11%	12%	12%	11%

Average maximum price (compared to MSRP)							
	Mon	Tue	Wed	Thu	Fri	Sat	Sun
07	74%	74%	49%	58%	61%	30%	35%
08	64%	68%	100%	69%	100%	58%	45%
09	100%	67%	82%	100%	84%	67%	82%
10	97%	100%	67%	95%	95%	98%	87%
11	85%	68%	80%	74%	72%	73%	62%
12	72%	83%	65%	96%	62%	98%	70%
13	72%	69%	64%	64%	100%	61%	82%
14	79%	68%	81%	82%	74%	73%	82%
15	70%	75%	71%	63%	65%	59%	75%
16	77%	69%	56%	66%	96%	66%	76%
17	81%	100%	75%	100%	61%	58%	95%
18	79%	100%	80%	100%	100%	78%	56%
19	100%	95%	100%	100%	100%	100%	97%
20	100%	100%	81%	100%	100%	100%	99%
21	100%	60%	96%	100%	100%	98%	100%
22	24%	39%	87%	55%	82%	75%	92%
23	36%	47%	35%	52%	100%	53%	100%

Figure 3. Average and maximum item prices throughout the day.

Our second hypothesis was that temporal clustering patterns, especially given the competitive arousal dynamics discussed previously, could lead to higher item prices in days and times when there is more activity. To this end, we examined the minimum, maximum, and average prices paid by the users in auctions closing at different times on different days of the week. Specifically, we considered the 30 most sold items in three different price ranges, that is, low (i.e., \$3-5), medium (i.e., \$20-50), and high (i.e., \$150-300). Our data suggest that while temporal patterns in bidding activity are evident, they do not necessarily translate into price escalation. Figure 3 reports the aggregate findings. On the left, it shows the average price paid by the winner compared to the manufacturer's suggested retail price (MSRP). The data show a weak positive correlation (i.e., r=0.27) between the temporal clustering of users' activity and the average price. Also, Figure 3 depicts the maximum price the user paid based on the day and time, which shows a positive correlation (i.e., r=0.55) with the temporal clustering shown in Figure 2. Average and maximum prices also show a mild positive correlation (i.e., r=0.52). Therefore, based on our findings, our initial hypothesis is rejected, that is, users do not pay a higher price on average in times with higher activity, competition, and competitive arousal, which contradicts previous studies [11] [12] [13] [14] [15] and, in general, notions about auction dynamics.

Nevertheless, this phenomenon could be explained by the fact that the final price is influenced by other factors related to the item itself (e.g., availability), the value bidders assign to each item or other dynamics. Although the average transaction price may not significantly fluctuate based on the auction's closing time, certain time windows exhibit a heightened propensity for bidders willing to pay more for an item. This difference suggests that although a bidder's overall risk of paying a higher price does not uniformly change based on the time of day, the competitive environment during peak times may be more intense. These peak periods might attract bidders prepared to place higher bids due to various motivations such as urgency, competitive arousal, or less price sensitivity.

C. Overbidding

The description of most items auctioned on the website (i.e., more than 17.5 million items, representing over 67% of the items listed) shows the MSRP. The MSRP shown on the website originates from e-commerce platforms such as Amazon.com and Walmart.com, and, thus, it can be assumed to be accurate though it may occasionally diverge from the item's true market value.

In more than 270,000 instances over the website's lifetime (i.e., nearly 1.5% of all transactions), approximately 25,000 buyers (i.e., 7% of all registered users) placed a winning bid higher than the item's MSRP. Specifically, nearly 246,000 unique buyers paid more than the suggested market value for items categorized as refundable, representing 92% of the overpaid items (see Figure 4). However, according to the website's terms and conditions, buyers get a refund only if evidence of damage, missing parts, or inaccurate product description is reported at pick-up. Furthermore, almost 24,000 unique users won the remaining 20,000 overpaid items categorized as not refundable, even in the presence of evident issues. This dynamic is counterintuitive, especially considering that the same products bought on e-commerce stores at the shown MSRP are usually eligible for free returns and refunds over a period ranging from 15 to 90 days. Several theories might explain this contradictory user behavior:

- Lack of knowledge of the website's operation, including user interface, refund rules, terms of service, and dynamics, rather than irrational behavior. For instance, this would imply that most individuals who engage in overbidding are novice users. However, the data show that over 70% of the users who paid for items more than the MSRP were also active in previous auctions, and over 50% had won other items. This could indicate that individuals engaging in overbidding are not novice users but are not fully aware of the terms and conditions of the platform. For instance, consumer misperceptions of risk and reward might explain the higher overpayments for items associated with the "refundable" label. Knowing that an item is refundable may lower the perceived risk, encouraging higher bids. The imbalance in refundable and non-refundable items might explain this dynamic. Also, the divergence between the two categories over the years might result from users becoming more aware.

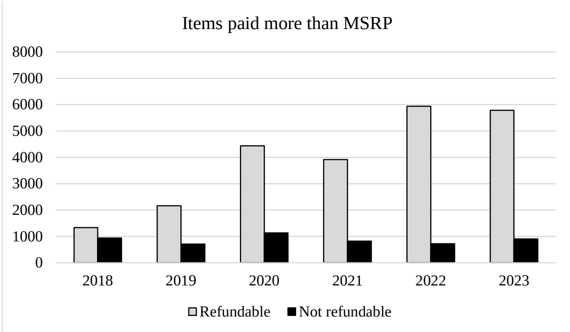

Figure 4. Items paid more than the shown MSRP.

- Information asymmetry, search cost, and availability of alternatives. The occasional divergence of MSRP from the true market value might create an information asymmetry where buyers are not fully aware of the item's actual value and do not trust the shown MSRP as an accurate proxy for market price. Also, users might not search for additional information or alternatives [19].

- Urgency and convenience. Users might engage in overbidding driven by the immediate need for an item or the logistical simplicity of consolidating pickups. As a result, the additional cost is perceived as an acceptable trade-off.

- Herd behavior or "winner's curse". As an extreme case of competitive arousal, bidders might overvalue items due to the competitive nature of auctions, leading them to bid higher than the MSRP. Further research is needed to investigate specific categories that might exhibit these dynamics due to factors such as novelty, scarcity, or desirability.

- Bidding addiction. Although further research on the behavior of individual bidders is required, a potential root cause could be that auctions tap into the same psychological drivers as gambling, with the thrill of bidding and the potential to "win" an item fueling behavior.

V. CONCLUSION AND FUTURE WORK

In this paper, we presented a preliminary study of three dynamics emerging from data representing five years of activity on an auction website. Our research analyzed patterns of competitive arousal, temporal clustering, and overbidding to gain insights into the factors influencing bidding strategies and, most importantly, identify aspects that need additional research. Given the data volume and the ongoing activity of the auction website, research on the dataset requires an incremental approach. Nevertheless, it provides significant analytical advantages compared to the data analyzed in other published works: (1) contains actual transactions instead of simulated data, (2) enables vast longitudinal studies, and (3) provides a focus on bidders' behavior in contrast to two-sided marketplaces such as eBay, where seller dynamics introduce more layers of complexity.

Our findings on competitive arousal highlight a clear pattern of intensifying bidding behavior as auctions approach their conclusion, with a significant 48.39% of bids occurring towards the closing time. This phenomenon might be driven by website features (e.g., watchlists and notifications) that will be investigated in a follow-up study. Interestingly, only a small number of early bidders remain engaged until the end, suggesting that most users observe the items before strategically placing a bid near the end.

Analyzing competitive arousal enabled us to scaffold our hypotheses on temporal clustering. Our study found that user activity varies during the day, with peak bidding activity in the evening. Intuitively, this pattern indicates a strong influence of daily routines on bidding behavior, with users more actively participating outside conventional working hours. However, our study rejected the hypothesis that temporal clustering affects the average price, showing only a mild positive correlation with the prices paid by item winners, in contrast with previously published literature. This suggests that while time of day influences bidding activity, it does not uniformly lead to higher prices, pointing to a more complex interplay of factors. This is especially significant given our results in terms of competitive arousal.

Finally, we studied overbidding. Our initial findings show that this practice occurs in a limited percentage of transactions, suggesting a range of underlying factors, from lack of platform knowledge to the psychological allure of winning, requiring follow-up validation studies.

Our study has several limitations, including reliance on secondary data. Despite its breadth and depth, covering several years of auction activity, our dataset does not contain any demographic information or fully captures the entirety of user interactions and behaviors on the website. For instance, the lack of information about users' watchlists may result in speculations on the true nature of bidders' engagement throughout the timeline of an auction. Furthermore, the exploratory nature of our work, which resulted in the analysis of a subset of the data only, may influence the generalizability and interpretation of the findings. Additionally, complex psychological and social factors driving bidding behavior, such as the winner's curse and herd behavior, are inherently challenging to measure directly, and any interpretations are necessarily inferential, highlighting the need for further research incorporating primary data collection, experimental designs, or additional longitudinal studies to validate and extend these findings. The rich features of the dataset will support additional studies in our future research roadmap, which will focus on aspects including the following: (1) competitive arousal based on product availability; (2) temporal clustering based on a more granular analysis of item categories, products, and MSRP; (3) bidding strategies and outcomes based on minimum increment and maximum bids; (4) game-theoretical modeling of auctions involving the same products as repeated games; (5) auction closing strategies and sniping, with specific regard to the amount and timing of bids; (6) behavior based on geographical availability of items; (7) behavior based on user profiling; (8) behavior modeling based on machine learning; (9) presence and impact of item allocation strategies (by the platform); (10) user behavior with respect to price fluctuations across auctions; and (11) key features of the user interface, including the watchlist, impacting information asymmetry.

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