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Rational Bidding Meets Emotional Viewing: The Landscape of English Auction Livestreams in The Age of Algorithms

Tawaran Rasional Bertemu Penonton Emosi: Landskap Siaran Langsung Lelongan Inggeris di Era Algoritma

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ABSTRACT

English auctions, renowned for their blend of economic and entertainment elements, serve as dynamic platforms for selling goods. This research, grounded in Game Refinement Theory and the Motion in Mind Model, delves into bidder behavior to elucidate its impact on entertainment perceptions at varying levels of rationality. Our findings uncover distinct patterns of behavior across completely irrational, partially rational, and fully rational bidders, highlighting how these differences influence the entertainment value. Specifically, we examine participants' bidding frequency, proficiency in information gathering, enforcement of beliefs, and rationality, all of which are perceived differently by viewers of live-streamed auctions. The study significantly deepens our understanding of English auctions' psychological and strategic foundations. It gives auction organizers crucial insights into enhancing economic and entertainment outcomes, emphasizing the strategic importance of timing and patience in bidding. This multifaceted approach not only underscores the economic indicators such as price dynamics and bidder competition but also integrates social and psychological perspectives, revealing how social interactions and cognitive processes influence auction dynamics and participant behavior. Such insights are invaluable for designing auctions that are both economically efficient and engaging, ensuring a balanced experience for all participants.

Keywords**:** English auctions, Game refinement theory, Motion in mind model, Bidder rationality, Entertainment perceptions, Cognitive psychology

ABSTRAK

Lelongan Inggeris, yang terkenal dengan gabungan elemen ekonomi dan hiburan, berfungsi sebagai platform dinamik untuk menjual barangan. Penyelidikan ini, berdasarkan Teori Penyempurnaan Permainan dan Model Gerakan dalam Fikiran, menyelidiki tingkah laku pembida untuk menjelaskan kesannya terhadap persepsi hiburan pada tahap rasionaliti yang berbeza. Penemuan kami mendedahkan corak tingkah laku yang berbeza di kalangan pembida yang tidak rasional sepenuhnya, sebahagian rasional, dan sepenuhnya rasional, menonjolkan bagaimana perbezaan ini mempengaruhi nilai hiburan. Khususnya, kami meneliti kekerapan pembidaan peserta, kecekapan dalam pengumpulan maklumat, penguatkuasaan kepercayaan, dan rasionaliti, yang semuanya dilihat berbeza oleh penonton lelongan yang disiarkan secara langsung. Kajian ini secara signifikan memperdalam pemahaman kita tentang asas psikologi dan strategi lelongan Inggeris. Ia memberikan pandangan penting kepada penganjur lelongan untuk meningkatkan hasil ekonomi dan hiburan, menekankan kepentingan strategik masa dan kesabaran dalam pembidaan. Pendekatan pelbagai aspek ini bukan sahaja menekankan penunjuk ekonomi seperti dinamika harga dan persaingan pembida tetapi juga mengintegrasikan perspektif sosial dan psikologi, mendedahkan bagaimana interaksi sosial dan proses kognitif mempengaruhi dinamika lelongan dan tingkah laku peserta. Wawasan seperti ini amat bernilai untuk merancang lelongan yang cekap secara ekonomi dan menarik, memastikan pengalaman yang seimbang untuk semua peserta.

Kata kunci: lelongan Inggeris, teori penyempurnaan permainan, model gerakan dalam fikiran, rasionaliti pembida, persepsi hiburan, psikologi kognitif

INTRODUCTION

Auctions have been an indispensable part of the economic system for a long time, with ancient origins dating back to 500 BC in places like Babylon (Baranwal et al., 2018). Among various auction formats, descending (Dutch), ascending (English), and sealed bidding (including first-price and second-price) stand out as the most prominent methods (Plott, 1997). Compared to direct sales, the primary allure of auctions lies in their transparency regarding item value and the competitive landscape among potential buyers. The uniqueness of auctions highlights the intricate resource allocation and subtle price determination nuances (Vickrey, 1961).

Moreover, the inherent competitiveness of auctions often sparks emotions, leading to phenomena such as "auction fever." Bidders acquire desired items through participation and showcase their prowess and abilities. The integration of auctions and game theory elucidates the interactive dynamics among participants. This non-cooperative finite game process embedded within bidding has long been a topic of extensive research (Majadi et al., 2017).

Board games like "Power Grid" and "Modern Art" incorporate the bidding process of English auctions (Clair, 2021). In "Power Grid," players purchase electrical equipment through auctions and compete for resources, whereas in "Modern Art," players act as art brokers, engaging in art auctions with others (“Power grid,” https://boardgamegeek.com/boardgame/2651/power-grid). Both games emphasize the significance of strategy and bidding decisions, offering players a taste of the core charm of English auctions.

As the influence of auction theory expands, there is a growing interest in understanding the entertainment value of auctions. This blend of entertainment with strategic decisions illustrates the dual role of auctions: on the one hand, they provide a platform for economic transactions, and on the other, they serve as venues for social interactions and strategic confrontations. With the rise of online and live-streamed auctions, the game-like nature, filled with strategy, excitement, and skill challenges, becomes increasingly apparent (Fan et al., 2022). This intersection between entertainment and strategy paves the way for new research explorations. In addition to their economic role, auctions serve as rich social and psychological arenas. Participants engage in transparent economic transactions, complex social interactions, and psychological processes (Smith, 2002).

Regarding the roles of strategy and skills, especially in the intertwined context of entertainment and decision-making, the game refinement theory and the motion-in-mind framework offer invaluable research perspectives. This paper aims to delve deeply into these theoretical frameworks, shedding light on the interplay of strategy, skills, and entertainment in English auctions and their significance in understanding contemporary auction phenomena.

RELATED WORK

1. Auction Theory and English Auctions.

Auctions involve transactions that sell goods and services like art, real estate, stocks, and telecommunications licenses (The Committee for the Prize in Economic Sciences in Memory of Alfred Nobel, 2020). Auction markets relate to economics and game theory (McAfee and McMillan, 1987), introducing concepts like market equilibrium and competition, facilitating a richer understanding of auction mechanisms and principles of resource allocation (Vickrey, 1961). Auction theory studies auction markets, including the behavior of buyers and sellers and the market's nature. John Harsanyi's work in auction theory paved the way for Paul Milgrom and Robert Wilson (Harsanyi, 1986). Their research led to significant advancements in auction theory and market design, for which they were awarded the 2020 Nobel Memorial Prize in Economic Sciences (The Committee for the Prize in Economic Sciences in Memory of Alfred Nobel, 2020). Their pioneering insights into auction formats and strategies have become fundamental in contemporary auctions, addressing critical challenges such as setting initial prices and guiding bidders to determine their maximum bid.

Economic and game theories provide analytical frameworks to understand the complexities of auction markets. Game theory is a valuable tool for studying strategic decisions and behaviors among auction participants. Scholars have used it to analyze auction dynamics and identify optimal bidding strategies in the face of unobservable values. The research aims to uncover the attributes of auction markets and the best strategies for bidding (Wilson, 1992). English auctions are open ascending auctions where the auctioneer starts with a low bid and gradually increases it until no more bids are made (Neeman, 2003). The highest bidder wins, and the mechanism is transparent to participants. Although extensively studied, there are still nuances to be explored, such as bidding strategies, information asymmetry, and fairness. Given their use in real-life settings, understanding English auctions is vital to academics and practitioners.

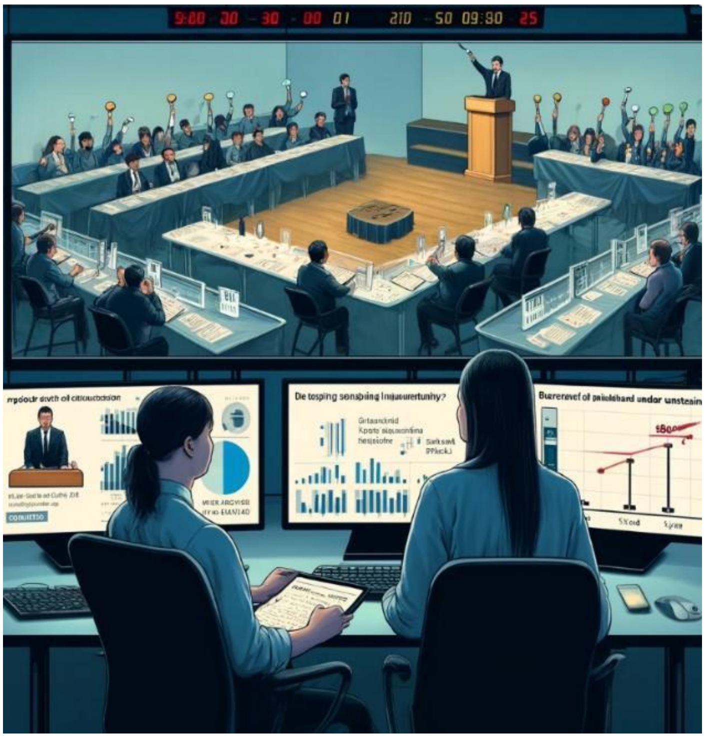
2. Game Refinement (GR) Theory and Motion in Mind Framework.

Game Refinement (GR) theory, introduced by Iida et al. (2004), explains how uncertainty and complexity affect player evaluations. It has applications beyond gaming, including commerce and education. Based on the anchoring effect, players rely on familiar analogies to decide. The GR theory helps understand player progression and uncertainty reduction through game mechanics and links these factors to game quality evaluation. Subsequently, the motion-in-mind framework was built upon the GR theory by linking game velocity, player success rates, and perceived game quality (Iida et al., 2020). It introduces the concept of potential energy and recognizes that players seek a balance between challenge and ability. The framework is relevant in English auctions as it is considered a stochastic game, where randomness plays a significant role in players' decisions and outcomes (Iida et al., 2020) (Khalid and Iida, 2021).

In studying English auctions, we adopt two primary perspectives: that of an external observer and an internal participant. From the viewpoint of the external observer, such as researchers or game designers, the focus is primarily on the overall auction behaviors and characteristics of the participants without delving into the specific winner or their decision-making process. Conversely, the internal participant's perspective emphasizes how individual participants observe their competitors and make bidding decisions based on their evaluations. This study predominantly employs the perspective of the internal participant for data simulation, delving deeply into participants' valuation, decision-making, and cognitive behaviors under incomplete information games and uncertain conditions. Subsequently, we observe and research how these simulated behaviors result in observable data changes from the external perspective.

As shown in Figure 1, a researcher observes and analyzes the auction behavior in a high-tech control room. Traditionally, game behaviors are analyzed through post-match reviews. This study aims to establish a model that correlates participants' decisions, our behaviors, and the game data that external viewers observe. This not only provides a foundational analytical model for scenarios like auctions, which possess economic, competitive, and gaming characteristics, but also serves as a basic analytical tool for new, game-like phenomena in the era of live streaming, such as sports broadcasts, gaming streams, and reality competition shows, thereby laying the groundwork for subsequent research.

Figure 1. Monitoring the Auction Process in a High-Tech Control Room



Note：Designed by the senior author and generated using ChatGPT4.

The connection between GR theory and the motion-in-mind framework offers a powerful tool for investigating complex game scenarios, such as English auctions. While the Game Refinement Theory focuses on reducing uncertainty, the Motion in Mind model emphasizes the dynamics of information acquisition. This condition makes them ideal for analyzing the inherent complexity of the English auction process. This study can create a comprehensive framework for understanding player behavior, decision-making strategies, and outcomes in

English auctions by adopting these theories. In addition, this study explores the subtle interactions among players, the perception of value, and the competitive dynamics of auction environments.

GAME REFINEMENT THEORY AND MOTION IN MIND FRAMEWORK

Player evaluations in games are shaped by game complexity and information uncertainty (Iida et al., 2004; Iida et al., 2020). Aligning them with game mechanics with physical laws to steer players' cognition leads to the GR theory and its subsequent Motion-in-Mind framework. These mathematical models gauge the aspects of the game-playing and its entertainment values, which relates to the information growth with time, given as Eq. (1). However, given that game-playing may involve uncertainty, a realistic information growth with time is reformulated as given by Eq. (2).

$$x'(t) = \frac{n}{t}x(t) \tag{1}$$

$$x'(t) = \left(\frac{t}{T}\right)^n \tag{2}$$

Furthermore, the game refinement metric is derived by examining the second derivative of the information Eq. (3). It is denoted as the acceleration of information growth. Generalizing the game progression to various game types and structures, the game mechanisms can be defined as Eq. (4), where G and T were the number of options/decisions and game length/steps, respectively.

$$x''(t) = \frac{n(n-1)}{T^n}\, t^{n-2} = \frac{n(n-1)}{T^2} = a \tag{3}$$

$$x(t) = v = \frac{G}{T} = \frac{1}{2}\frac{B}{D} \tag{4}$$

Considering similar metric, in the context of the reward frequency N, an additional measure can be defined as Eq. (5). and the third derivatives were defined as Eq. (6). Then, GR and AD, which quantify entertainment experiences such as thrill and unpredictability, given by Eq. (7) and Eq. (8), respectively, in games. Table 1 shows the measures of game refinement for board games. For sophisticated board games such as Chess, Shogi, and Go, a reasonable zone for the acceleration ($\sqrt{a} = GR$) and jerk ($\sqrt[3]{j} = AD$) was found, which is between $GR \in [0.07, 0.08]$ and $AD \in [0.045,\ 0.06]$, respectively.

$$N = \frac{1}{v} \tag{5}$$

$$j = \frac{6G}{T} = \frac{3B}{D} \tag{6}$$

$$GR = \sqrt{a} \tag{7}$$

$$AD = \sqrt[3]{j} \tag{8}$$

Table 1. Measures of Gr and Ad For Popular Board Games (Gao et al., 2022 Khalid and Iida, 2021)

	B	D	$\sqrt{a} = GR$	$\sqrt[3]{j} = AD$
Chess	35	80	0.074	0.059
Shogi	80	115	0.078	0.054
Go	250	208	0.076	0.044

1. Analysis of English Auctions.

The main challenge in modeling and analyzing English auctions lies in their randomness. Focusing on this distinct characteristic, the game tree structure, and GR theory were utilized to guide the analysis of the auction system, where traditional formulation of the information growth (or velocity) of the said theory requires some revision. In this context, the model must consider the relationship between various decisions, the progression steps, and the participant numbers in the auction. The board game model (denoted as BD model) of the GR theory was adopted to accommodate the complexities of English auctions, allowing the construction of the game tree based on three key decision points in the auction process: (1) Accepting the starting price and deciding whether to participate in the auction, (2) whether to choose to raise the price in each round and (3) When to choose to withdraw from bidding. This perspective helps better understand the actual bidding behavior and the dynamics of English auctions.

According to the GR theory, the depth of the game progress is represented by D. It is equivalent to the collection of all possible decision-making actions of participants formally participating in auctions, raising prices, and choosing to withdraw from bidding, i.e., the total of all decision opportunities at three key decision points, or decision opportunity space (S_t) (see Eq. (9)). Meanwhile, the average options (or width) of the game tree structure is given by B. This situation can be regarded as all possible actions of participants in each round (h) as a possible state. Then, all possible states are compiled into a state set (A_h). Thus, B computes the number of bidding opportunities by each participant in each round. In other words, B defined the average number of elements in the action set of all rounds, given by Eq. (10).

$$D = S_t = N_t + 1 + 1 \tag{9}$$

$$B = \frac{1}{N_t}\sum_{j=1}^{N_t} |A_h| = Average(|A_h|) \tag{10}$$

Then, the speed of the auction game can be defined as Eq. (11). Subsequently, the GR and AD of the English auction can be derived as given by Eq. (12) and Eq. (13), respectively.

$$v = \frac{1}{2}\frac{Average(|A_h|)}{S_t} \tag{11}$$

$$GR = \frac{\sqrt{Average(|A_h|)}}{S_t} = \frac{\sqrt{B}}{D} \tag{12}$$

$$AD = \sqrt{\frac{3 \times Average(|A_h|)}{{S_t}^3}} \tag{13}$$

Table 2. Comparison of Variable Applications between Traditional Game Theory and English Auction Analysis

Variable	Meaning in Traditional Games	Meaning in English Auctions
n	--	Number of bidding choices available at any point during the auction.
t	Current step or stage in the game.	Current round or phase in the auction process.
T	Total duration of the game in terms of rounds or steps.	Total length of the auction from start to finish in rounds or steps.
G	Total decisions or actions taken throughout the game.	The total number of decisions made throughout the auction, specifically the number of bids placed by each participant.
B	Average choices available to a player in each round.	The options available to participants in each round include: bidding, stopping, or observing.
D	Depth （Length） of the game, indicating complexity or the range of decision-making points.	Depth （Length） of auction strategy, representing all possible decision points from beginning to withdrawal.
St	--	Set of all possible auction decisions up to time t, defining the decision space.

Note: Independently drawn by the senior author.

Figure 2. Diagram of Strategic Choices and Exit Timing in the Auction Process

2. Experiment Design and Data Collection

We have curated a dataset of contemporary art auction prices between 2020 and 2023. The collection includes guide prices, exhibition valuations, and other relevant information from that period. We randomized the data to simulate a practical auction setting. The dataset combines structured data, such as prices, with unstructured data, which includes bidder actions and sentiments. We aggregated the data from various digital and physical sources and used multiple databases to analyze past bidding tendencies and auction outcomes.

Every piece of data was carefully preprocessed to ensure quality and coherence. After data consolidation, we simulated bidder behaviors and predicted observable outcomes from an external perspective. Insights gained from these predictions were used to adjust the behavior parameters of AI participants, thereby refining our model. We also applied inferential statistics to identify patterns and cross-verified them with our theoretical frameworks.

Our experiment comprises two modules. The first module is responsible for gathering information and assessing prices, while the second is dedicated to bidding. The study underscores the importance of beliefs in making auction decisions and investigates how these beliefs change with new information. Our goal is to provide a more comprehensive understanding of auction bidding dynamics.

3. Simulation Scenarios

English auctions' bidding behaviors are modeled using GR theory and the motion-in-mind model. Participants collect information and estimate prices, facing challenges such as bias and incomplete information. The auction is like poker, with bidders adapting to their opponent's moves. This experiment examines how bidders' behavior affects observers' enjoyment. The simulation involves stratifying the participants into three categories to reflect their decision-making dynamics better:

1) **Novice Bidders**: Fresh to the auction arena, they predominantly lean on chance, lacking substantive skills in gathering information or valuation. In this context, the participants estimate item value and bid up to a random asset fraction, with the flexibility to adjust based on competing bids (Algorithm 1).

Algorithm 1: Restricted Estimate Bidding Adjustment (Novice Bidders)

```
Input: Participant's public and private information: participant's estimate of the
item's value
Output: Final bid placed by the participant
        available_assets ← random value between 0 and 1 ; /* Generate a random maximum
        asset value*/
        α ← participant's estimate of the item's value
        While other participants continue to bid do
                β ← available_assets × α; / *Calculate maximum bid based on random maximum asset
                value */
                If other participants have bid then:
                        ▪ α ← 1.1 × α;   /Adjust estimate upward by 10% if others are
                          bidding */
                   End
                If β exceeds estimated value then:
                        ▪ bid ← α;   /* Submit bid equal to estimated value */
                   End
                Else:
                        ▪ bid ← β; /* Submit bid equal to maximum bid*/
                   End
```

```
        available_assets ← available_assets – bid; /*Update available assets based for the
        bid*/
    End
    Return the final bid placed by the participant
```

2) **Bounded Rationality Bidders**: Having previously dipped their toes in English auctions, they showcase basic information-collecting and evaluation skills. They hold certain auction beliefs, but their choices can still be influenced by peers. In this context, two modules were incorporated. Module I focuses on simulating the information collation and valuation based on sample data, imbibing cues from auction theory and studies on English auction efficiency (Algorithm 2). Meanwhile, Module II recreates the auction atmosphere where various bidders vie for a singular item, with each participant coded to ensure active engagement (Algorithm 3 and Algorithm 4).

Algorithm 2: Simulation of the information gathering and valuation process in an auction

```
Input: Auction prices of contemporary art from 2020 to 2023
Output: participants.count, participant.estimates, common_price
for sample ∈ random_samples(dataset, 100) do
    participants.counts ← extract_participants.counts(sample);
    guidance_price ← extract_guidance_price(sample);
    exhibitions ← extract_exhibitions(sample);
    history ← extract_history(sample);
        for participants.count ∈ participants.counts do
            participant.estimates ← empty list;
            for j = 1 to participants.count do
                standard_estimate ← calculate_standard_estimate(guidance_price, exhibitions, history);
                coefficient ← generate_coefficient();
                participant_estimate ← calculate_participant_estimate(standard_estimate, coefficient);
                participant.estimates.append(participant_estimate);
            End
            common_price ← calculate_common_price(guidance_price, exhibitions, history);
            write_to_file(participants.count, participant.estimates, common_price);
        End
End
```

Algorithm 3: Auction Bidding Process Simulation

```
Input:
        Number of participants (num_participants)
        List of values (value_list)
        Common values (common_values)
Output:
        Participants' details, winner, winning price, total bids,
        maximum/minimum/average bids, deal difference
Initialize empty list: participants;
For i = 0 to num_participants do:
      preference ← random value from [p1, p2, p3, p4, p5];
      Create participant with id, value, bid details, preference;
      Add to participants list;
End
Set common value, initialize winner and winning price;
For i = 0 to 10,000 do
    ;                              /*Simulation loop*/
    For each participant in participants do:
         If random value between 0 and 1; participant's preference then:
                           Update participant's bid details;
         End
    End
End
Calculate final results;
Return Final results;
```

Algorithm 4: Bidder Belief Failure Simulation

Input: Number of participants n, Starting bid price b_0, Guide price g, Historical information H, Exhibit information E

```
Output: Winning participant p, Winning bid price b_p
Initialize participants using H, E, g;
Set current bid price b ← b_0, auction end flag end ← False;
While ¬end do:
For each participant i do:
Adjust and submit bids;
End
Determine the winner and update values;
End
Return p, b_p;
```

3) **Rational Bidders**: Their bidding behavior follows the Bayesian Nash equilibrium principle. Not only do they have a profound understanding of the strategies of other bidders, but their assessment skills have also been trained and optimized using genetic algorithms. These bidders employ a Bayesian Nash equilibrium approach merged with a Monte Carlo search technique (Lopez-Gonzales et al., 2020) (Algorithm 5). They firmly believe in their strategies, unaffected by peer dynamics. Judgment and credit assessment modules at the highest level were incorporated for an immersive simulation.

Algorithm 5: Process of Monte Carlo Tree Search and Bayesian Nash Equilibrium Algorithms

```
Input: Number of iterations N, Number of rounds R, Initial auction parameters, Pre-trained
    model
Output: Optimal strategy for each participant
Initialize simulation;
For n = 1 to N do:
    Initialize auction;
    For r = 1 to R do:
        Use pre-trained model to determine strategies and update values;
    End
End
Return Optimal strategy;
```

RESULTS ANALYSIS AND DISCUSSION

In this section, the analysis of the results involving the relationship between different behaviors of bidders across different levels of rationality and their influence on the entertainment value perceived by the audience, with the aid of our simulation data (Table 2). Comparison between novice, bounded rationality, and rational bidders suggests that bid frequencies and magnitudes, represented by variables such as B, D, and V, correlate with the suspense factor, thus influencing entertainment value. The results also indicate that the Growth Rate (GR) tends to fall within a comfortable range ($GR \in [0.07, 0.08]$).

From an external observation perspective, novice bidders with a $GR = 0.1287$, $GR = 0.1287$, are significantly above the comfort zone, suggesting that the pace of English auctions may seem relatively fast for beginners. Conversely, rational bidders who employ the Bayesian Nash equilibrium strategy show a GR = 0.0686, slightly below the comfortable range, hinting that English auctions might appear overly simplistic or unengaging to them from an external viewpoint, for participants exhibiting bounded rationality, the observed $GR \approx 0.106$. This behavior embodies the concept of 'bounded rationality' in economics, signifying that these individuals might gather extensive information and make frequent bids, resulting in a rapid auction pace.

Table 2. Auction Simulation Data with Different Bidder Levels

Level	B	D	V	GR	j	AD	N
A	5.125	17.585	0.146	0.1287	0.0028	0.1414	6.86
B	3.422	17.453	0.098	0.1060	0.0019	0.1245	10.20
C	1.455	17.584	0.041	0.0686	0.0008	0.0929	24.17

A : Novice; B : Bounded rationality; C : Rational;

The study found that the relationship between game complexity (GR) and fluctuation (AD) plays a significant role in determining player engagement and potential addiction (Gao et al., 2022). The game becomes engaging when $GR = AD$ where players may become addicted. The researchers also discovered that the game's peak addiction occurs when reward frequency (N) and B (the average number of actions available to participants in each round of the auction) are set to 9 and D (the total number of decision-making actions available to participants throughout the auction) is around 40.

The study also found that the game's optimal addiction occurs when $GR = AD, B = 9, D \in [37.5, 42.85]$, while the game velocity and reward frequency were $V \in [0.120, 0.105]$and $N \in [8.333, 9.522]$, respectively. Considering the live broadcast of English auctions, this experiment revealed that to achieve the most engaging game dynamics, 18 to 20 participants are optimal for novice bidders, resulting in 35 to 43 bidding rounds. This situation offers a balance between entertainment value and game intensity. For those at the bounded rationality level, having 27 to 32 participants is ideal, while for bidders strictly adhering to the Bayesian Nash Equilibrium, approximately 57 participants are required.

Table 3. Optimal Number of Participants for Different Bidder Levels under Specific Conditions

GR = AD, B = 9, D ∈ [37.5, 42.85]	
Bidder Level	**Number of Participants**
Novice Bidders	18 to 20
Bounded Rationality	27 to 32
Rational Bidders	≈ 57.23

Several aspects posed as the entertainment value in the auction. First, the value of unique items being auctioned cannot be accurately measured but will likely influence how the audience perceives them. Second, the competition between bidders adds to the entertainment factor of the auction, as observed through the behavior of rational bidders. Third, though not quantifiable, emotional attachment to specific items or bidders also contributes to entertainment. Finally, the pace of the auction may also appeal to the viewers' desire for knowledge and cultural insight, making it more engaging.

Different bidder categories use varying strategic methods, influenced by their unique psychological processes. Waiting, bidding at the right moment, and retracting bids at the optimal time are crucial for English auction participants. Novice bidders use reactive strategies influenced by competitors, leading to high GR values. Rational bidders are methodical and have lower GR values due to intentional pacing and strategic optimization. Bidders with bounded rationality exhibit a mix of these behaviors due to cognitive limitations, resulting in distinct GR values and bidding patterns.

The English auctions were compared with other mechanisms to understand bidder behaviors. Milgrom (1989) noted that public pricing is typical for standard goods (P. Milgrom, 1989). Although English auctions are effective, exploring other sales mechanisms like open pricing provides a more comprehensive context. The difference between English auctions and other mechanisms is significant, especially in situations without reserve and open prices, giving us a detailed perspective on when each is most efficient.

Moreover, the relationship between bid frequencies, magnitudes, and entertainment value suggests that participants are driven by the desire to win and the thrill and suspense inherent in the auction process. Simultaneously, when bidders seek the social and advertising value of participating in an English auction, such as representing a company, they need to consider the entertainment value of the auction broadcast alongside its economic worth. This confluence of strategy and entertainment introduces a fresh perspective, indicating that English auctions aren't just economic transactions but also arenas of social and psychological engagement.

Real-world economies are resilient even as environments change. English auctions are economic structures and social constructs. They work effectively in diverse scenarios, demonstrating their broad applicability. This study provides valuable insights for both auction organizers and participants. It helps organizers design engaging auction mechanisms and reveals strategic tendencies that can improve participants' tactics. Additionally, it guides bidders in navigating English auctions with more finesse. Overall, the study highlights the significance of English auctions as economic, social, and psychological phenomena.

CONCLUSION

Using the GR theory and motion-in-mind framework, this study examined bidder behavior in English auctions to analyze their entertainment perceptions across different levels of rationality. Key findings were revealed:

1. Bidders' behaviors vary based on rationality levels: irrational bidders act randomly, and auctions move faster. Partially rational bidders observe others, and auctions are quick. Fully rational bidders follow the Bayesian Nash equilibrium strategy, and auctions are slow.

2. Through the lens of GR theory, it became evident that bid frequencies and magnitudes, and their relation to suspense, significantly influence entertainment value.

3. In the context of auction pace, the motion-in-mind framework sheds light on the perceptions between novice and rational bidders. Novice bidders, influenced by their immediate emotions and reactions, tend to perceive auctions as fast-paced, while rational bidders, who adopt a more calculated approach, perceive them as slightly simplistic.

4. An important factor in participants' auction performance is the skill of patience, which involves seeking the most appropriate time to bid, alongside other skills like belief and information gathering.

The research sheds light on the psychological and strategic factors behind bidder behavior in English auctions and the entertainment that auctions can bring to outside observers in the age of algorithms and live streaming. The findings are valuable to organizers for integrating economic and entertainment values. Auction organizers can use insights from GR theory and the motion-in-mind framework to customize auctions for optimal engagement. Bidders can refine their approach in future auctions and gain insights into their strategic inclinations and emotional motivations.

There are several areas for future research to explore. Firstly, researchers could investigate the intrinsic values of auctioned items and how they relate to the motion-in-mind framework, which shapes bidder behavior. Secondly, they could examine how emotional investments and biases, viewed through the lens of the GR theory, influence bidding patterns and auction outcomes. Lastly, comparing and contrasting English auctions with other sales mechanisms would be interesting to see what differences exist.

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