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Japan Advanced Institute of Science and Technology

Doctoral Dissertation

# From Economic Utility to Game Utility: A Serious Game and Leisure Economic Analysis of Auctions in the AI Era

LI SIQI

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# Abstract

This dissertation investigates the interdisciplinary application of auction theory, game theory, and behavioral economics through AI-driven modeling and simulation, leveraging advances in artificial intelligence (AI) and data science. Using Game Refinement Theory and the Motion in Mind framework, combined with extensive auction data, a dual-perspective model (internal and external perspectives) has been developed to analyze complex participant behaviors in auction environments. This model captures not only the economic utility of participants under rule-based constraints but also the game utility driven by non-economic motivations, positioning auctions as a unique type of economic game.

Over 10,000 auction items from major auction houses Christie's and Sotheby's (2020–2023) were collected and analyzed, with simulation techniques applied to model and optimize key auction dynamics. Findings reveal a strong negative correlation between auction velocity and price deviation across various price segments, highlighting the crucial impact of non-economic motivations (e.g., status signaling, social recognition, emotional investment) on participant decision-making. Furthermore, an AI-based simulation system was designed to optimize auction participant experience and market performance, using auction simulation algorithms and feedback loops to dynamically analyze participant behavior patterns. This system enables real-time simulation of bidding decision processes, improving the predictive accuracy for complex decision-making.

Technically, this research: (1) introduces a model of non-economic game utility to quantitatively analyze psychological and social motivations beyond economic utility, (2) develops an AI-driven dual-perspective simulation model linking "irrational behavior" of participants with overall auction dynamics, and (3) constructs an efficient data processing and simulation framework, combining game theory with AI to optimize auction systems. The results confirm the effectiveness of AI algorithms in modeling complex economic decisions and provide theoretical and empirical support for application to other interactive economic transaction systems.

This study contributes to the intersection of computer science, behavioral economics, and game theory, demonstrating the potential of AI and data-driven methods for simulating complex market dynamics and optimizing decision-making. Future applications of this model could extend to other economic game scenarios, providing deeper tools for modeling irrational behaviors in digital economic activities, supporting algorithm optimization, and guiding decision-making in real market contexts.

**keywords** Motion in mind, game refinement theory, Non-Economic Utilities, Auction design, Auction Simulation, gameplay incentives

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# Chapter 1

# Introduction

An auction is a resource allocation mechanism that determines the price and ownership of goods or services through competitive bidding. Auctions are typically defined by a set of rules, including the format of the bidding process, constraints on participants' behavior, and the method for determining the final price. Over millennia, auctions have evolved significantly, from their origins in ancient Babylon to the advanced, AI-powered platforms of today. These structured competitive environments play a significant role in economics and game theory, providing clear rules and measurable participant behaviors. Auctions are not just simple transactions but involve complex economic, psychological, and social dynamics that make them a valuable area of study. This dissertation investigates these dynamics, focusing on the intersection of artificial intelligence (AI), auction theory, and game theory, aiming to explore how irrational economic behaviors can be modeled and optimized using advanced computational tools.

## 1.1 Background and Motivation

In 2018, Open AI released the first version of GPT (Generative Pre-trained Transformer) [4], marking a significant milestone in deep learning in the field of natural language processing, and officially ushering in the era of large language models. The success of GPT demonstrated the powerful capabilities of pre-trained models with large-scale parameters in language generation tasks. Subsequently, in 2019, Google introduced BERT (Bidirectional Encoder Representations from Transformers) [5], further driving the development of large models and their widespread application in various natural language processing tasks. These models are based on the Transformer architecture, leveraging large-scale training data and computational resources to achieve unprecedented performance. In 2020, OpenAI released GPT-3, a model with 175 billion parameters, significantly improving the capabilities of large models and bringing the "era of large models" into the public eye [6]. GPT-3's exceptional performance in multi-task learning, text generation, and dialogue marked the widespread application of large models in complex tasks such as language generation, understanding, and reasoning. With the popularity of GPT-3, AI assistants have gradually become valuable tools in people's daily lives and work, transforming the way society operates.

In the era of artificial intelligence, we have the opportunity to re-examine various structures, data, and information transmission methods, particularly in the context of economic markets. These scenarios not only reflect cooperation and division of labor but are also closely related to human life. By studying each detail in depth, we can reconstruct systems in the digital world to achieve greater efficiency and fairness. Applying large-scale parameter models to economic game scenarios presents certain mathematical and engineering complexities. Each specific scenario requires careful, detailed analysis, and identifying universal principles calls for a step-by-step investigative approach. Auctions serve as an ideal model for studying economic games, given their clear rules, traceable processes, and quantifiable participant behavior. This makes them an excellent subject for modeling. After years of research, scholars have clarified that the auction process conforms to the Bayesian Nash equilibrium [7]. Nevertheless, integrating Bayesian processes or Markov processes with Transformer architectures remains a challenging task. On September 12, 2024, OpenAI released the GPT-o1 model, which showed significant improvements in mathematical reasoning. However, in certain specific economic fields, especially those involving human-to-human interactions, it is particularly important to conduct in-depth studies on the dynamics of interactions between individuals and between individuals and their environment. Measuring information within these interactions is also highly challenging.

Although economic game models are inherently complex, since Von Neumann and Morgenstern [8] introduced game theory, it has provided researchers with valuable tools to model complex problems. Through concepts such as 'expectation' and 'utility' under uncertain conditions, game theory has facilitated a better understanding of strategic situations. Von Neumann and Morgenstern's utility theorem (VNM Utility) defined rational choices as maximizing expected utility. While my study uses VNM utility, real-world behavior often deviates from rationality. I explore these habits that, though seemingly irrational, reveal underlying patterns. I call the total benefit or motivation from a game 'Game Utility.'.

This research selects auctions as the research subject, taking advantage of the clear boundaries of auction rules and building on existing research progress, such as auction theory and its developments [7, 9]. Auctions are an ideal model for studying economic games, with rules that have evolved over time to adapt to the demands of different eras and technologies. The history of auctions can be traced back to 500 BC in ancient Babylon [10], and they have evolved across cultures and eras. Two world-famous auction houses, Sotheby's and Christie's, were founded in 1744 and 1766, respectively [11]. As a historical and economic phenomenon, auctions have shaped trade and commerce from ancient times to the modern digital era. In the countless economic exchanges over its long history, auctions have evolved through interactions, achieving a balance of game dynamics and rules under the influence of the 'invisible hand' [12, 13]. These rules are crucial for resource allocation and price formation, attracting the interest of many economists and game theorists, including Nobel laureates [7, 14]. Auctions create a structured competitive environment, where bidders' decisions can be systematically analyzed to provide valuable insights into game theory and auction theory [15].

In the digital age, rebuilding auction systems in the digital world requires in-depth analysis of auction structures, data, and information transmission methods to achieve greater efficiency and fairness. However, reconstructing this system requires not only understanding ‘what’ it is but also delving into ‘why’ it works this way. Therefore, this study adopts a rigorous method by manually collecting real auction data and combining it with computer simulation and modeling. Using frameworks such as game refinement theory and motion in mind, this study measures the behavior of auction participants, reverses expectations based on game tree principles, and constructs an auction game model. To enhance the analysis, this research proposes innovative internal and external perspective modeling frameworks, establishing a feedback loop between these two perspectives. This dual-perspective approach provides a structured method for examining participant behavior, particularly when participants engage in certain irrational actions that deviate from economic rationality due to non-economic motivations. These models aim to offer a refined simulation tool for auction analysis, with potential to support future studies in understanding complex decision-making dynamics in interactive economic activities. Additionally, methods from game studies are applied to label and quantify participant behavior, especially for unstructured data, laying a foundation for integration with advanced computational models, including large language models.

In economic transaction scenarios, algorithms play a transformative role, not only facilitating processes but actively shaping the behavior of participants. This influence is particularly evident in systems like auctions, ad placements, or food delivery, where algorithms are designed to optimize outcomes. However, these algorithms do not solely serve humans, nor do humans merely follow algorithms; rather, participants often adapt to and, at times, influence these algorithms themselves. This mutual adaptation creates a dynamic relationship, where human behavior and algorithmic design interact in ways that evolve over time. In auction systems, for example, this interaction can lead to optimizations in both participant strategies and algorithm performance, reflecting a deeper level of engagement between humans and technology.

For an auction house to achieve higher revenues in a single auction, it must not only profit from the sale of individual items but also attract capable potential participants. This attraction is not only reflected in “economic utility” but also in the “conspicuous value” expected by participants seeking social recognition, the “entertainment value" aimed at bringing personal joy, or the "leisure game value" found in casual game studies. Building on von Neumann and Morgenstern's utility theory [16], I propose the concept of "Game Utility." Game Utility includes both **Economic Utility** (measurable financial rewards) and **Non-Economic Utility** (such as enjoyment, competition, and social recognition). While Economic Utility can be quantified, Non-Economic Utility, like dark matter, is less directly measurable. However, by analyzing deviations from standard economic models, we can calculate "irrational actions" stemming from Non-Economic Game Utility. The details of this approach are explained in Chapter 2.

These factors often lead to what behavioral economics terms "irrational behavior" [17]. Although such behaviors may appear random, they actually follow certain patterns due to the limitations of the participants' choices and the rules of the game [8]. By studying these patterns in depth, we can reveal the underlying logic. This discovery can not only be applied to auctions, but also provide new perspectives and research methods for the study of economics and behavioral economics in the era of live-streaming commerce. To this end, my research proposes concepts such as "game value," "game utility," and "non-economic game utility," which help model the "regular irrational behavior" of participants in economic games, such as card players, who engage in the activity driven by the pursuit of "non-economic game utility" or "game incentives." Throughout this paper, we refer to "non-economic game utility" as "non-economic utility" for simplicity.

While focusing on the microeconomic context of auctions, this research also considers how individuals navigate uncertainty in decision-making scenarios by balancing both "economic utility" and "non-economic game utility," a process that aligns closely with Herbert Simon's theory of bounded rationality [18], which describes how decision-makers operate within the constraints of limited information and cognitive resources. For example, in auction settings, participants can demonstrate behaviors driven by motivations beyond financial gain, such as social recognition or personal enjoyment. Although these behaviors may appear irrational, they often follow identifiable patterns influenced by game rules and individual constraints. By examining these patterns, this research aims to uncover underlying logics that contribute to both economic and non-economic motivations within competitive environments.

In his work *The Fatal Conceit*, Friedrich Hayek [19] warned of the dangers inherent in relying on universal rules or single, rigid principles to interpret complex human behavior. This approach risks suppressing the natural diversity and adaptability found in individual decision-making processes. Echoing this, as neuroscientist Li-Ming Wang [20] notes, "The danger of universal rules lies in the rigid attempt to interpret and guide all things with a single, unchanging principle. The overuse of probabilities can foster stereotypes, where broad generalizations obscure the nuances of specific cases. Additionally, when rationality is used to overshadow intuition and instinct, it risks ignoring the unique value of human individuality." This not only illustrates the challenges humans face when making choices under uncertainty but also highlights the difficulties decision-making AI encounters when addressing uncertain scenarios.

In economic simulations, acknowledging these insights is essential: individual behaviors, often non-rational and unpredictable, enrich the organic order of complex systems [21]. Through simulations that incorporate both structured models and spontaneous human elements, we can reveal how these individualistic and sometimes non-rational behaviors contribute to market dynamics, providing a more nuanced understanding of decision-making in economic environments. Through simulations and predictions, we can reveal the essence of real behavior in controlled or hypothetical environments.

Based on auctions, this research explores the so-called "irrational economic behaviors" driven by "game value." Although these behaviors seem irrational, they follow inherent patterns and regularities. This dissertation investigates the interdisciplinary application of auction theory, game theory, and behavioral economics through AI-driven modeling and simulation, leveraging advances in artificial intelligence (AI) and data science. Using Game Refinement Theory and the Motion in Mind framework, combined with extensive auction data, a dual-perspective model (internal and external perspectives) has been developed to analyze complex participant behaviors in auction environments. This model captures not only the economic utility of participants under rule-based constraints but also the game utility driven by non-economic motivations, positioning auctions as a unique type of economic game.

Additionally, this research aims to optimize economic decision-making models and improve market predictions through these analyses. The insights gained from these simulations can provide scientific support for real-world economic transaction strategies and policies, enhancing their effectiveness and reliability. Furthermore, by using analysis methods from game studies to label and quantify participant behavior, particularly in measuring unstructured and non-text data, this research lays the groundwork for future collaboration with other models, such as large language models.

This chapter reviews the historical evolution, theoretical foundations, and unique characteristics of auctions, analyzing their distinct role as research objects in economics, econometrics, and computational modeling. It also introduces the core hypotheses, research questions, and objectives of this study. By conducting an in-depth analysis of behaviors and decision-making processes within auctions, this research aims to uncover the patterns and logic of irrational behavior in auctions. Building on these insights, AI-driven simulations and the framework of Game Refinement Theory are applied to provide scientific foundations and new perspectives for optimizing auction systems and auction-like systems to enhance customer experience. Furthermore, this study proposes an innovative solution for customer flow planning in the fields of live-streaming economics and virtual transaction markets in the metaverse.

As such, auctions emerge as a uniquely complex and valuable area of study, providing insights that span economic, social, and psychological dimensions. By examining these intricate dynamics, this study aims to uncover the layered motivations behind participant behavior, using auctions as a gateway to broader explorations in economic games and decision-making processes.

## 1.2 Auctions as a Gateway to Understanding Economic Games: Exploring Irrational Behaviors

Auctions, as structured environments governed by clear rules and competitive dynamics, have a rich history that spans millennia. Originating in ancient civilizations such as Babylon and Rome, auctions were initially used for trading goods, land, and even people. One of the earliest recorded auctions, as described by Herodotus, took place in Babylon, where brides were auctioned to the highest bidder [10]. Over time, the evolution of auction rules has mirrored the growing complexity of economies, making auctions one of the most efficient mechanisms for resource allocation [22]. However, auctions are not purely economic mechanisms. They also embody intricate social dynamics, including elements of prestige, psychological engagement, and competition. This blend of economic and non-economic incentives makes auctions a particularly valuable model for research in game theory and behavioral economics.

The historical development of auctions, from ancient Chinese temple auctions [23] to the rise of major auction houses like Sotheby's and Christie's [11], demonstrates their adaptability to both economic and social shifts. In the Roman Republic, auctions were used to distribute war spoils and estates, further emphasizing their role in resource allocation [22]. This adaptability, coupled with the competitive nature of auctions, provides rich insight into participant behavior, which is crucial for understanding modern auction systems.

In contemporary settings, auctions serve as ideal models for studying economic games. Their structured and rule-based nature aligns closely with game theory principles, allowing for the analysis of both rational and irrational behaviors in competitive environments [7]. By tracing the evolution of auctions in the context of classical economic theories and the emerging concept of "game utility," this research underscores auctions as powerful tools for examining human decision-making in market environments. For a more detailed exploration of auction history, please refer to Chapter 2 and Appendix B.

### 1.2.1 Theoretical Frameworks in Auctions

With the advancement of economic theory, auctions have increasingly been studied through the lens of game theory, particularly focusing on the strategic interactions among bidders. The formalization of auction types by Vickrey [7] laid the groundwork for a robust field of research in both economics and game theory. Harsanyi's introduction of games with incomplete information further expanded the analytical tools available to economists studying auctions [24]. Detailed discussions on these theoretical frameworks can be found in Chapter 2 and Appendix C.

### 1.2.2 Psychological and Social Dimensions of Auctions

In addition to their economic function, auctions are also platforms for what Thorstein Veblen termed "conspicuous consumption," where individuals engage in purchasing to display wealth and status [25, 26]. This is particularly evident in high-profile art auctions, such as the sale of Leonardo da Vinci's *Salvator Mundi* for $450.3 million, which illustrates how auctions can act as stages for social capital display [27]. A more in-depth analysis of these psychological and social dimensions is provided in Chapter 2 and Appendix A.

## 1.3 Problem Statement

The digital transformation has reshaped auctions, introducing new variables such as algorithms, data transmission, and real-time decision-making processes. However, existing models for auction analysis often focus solely on economic utility, overlooking the complex psychological and social dimensions that influence participants' behavior. This gap presents an opportunity to apply AI and game theory frameworks to better understand the "non-economic utilities" driving participant behavior. This study will address the following questions:

**Research Question 1:** What factors contribute to the game appeal of auctions, and can traditional game research methods such as Game Refinement Theory and

Motion in Mind Framework be used to assess auctions as an economic game activity? How can Game Refinement Theory and Motion in Mind Framework be applied to evaluate this appeal?

**Research Question 2:** What strategies do auction houses use to enhance auction appeal? How do special items and changes in dynamics, like auction velocity and mass, enhanced participant experience and promote status signaling or conspicuous consumption?

**Research Question 3:** What impact do live-streamed auctions have on audience engagement? How do the boundaries between entertainment value and rational decision-making influence participants' behavior, and how can these elements be optimized to enhance the auction experience?

**Research Question 4:** What motivates participants to engage in activities when faced with initial uncertainty? How do economic utility and non-economic utility together influence decision-making in these contexts? Additionally, how can insights from economic structures contribute to the improvement of AI algorithms?

## 1.4 Theoretical Foundations

This study extends the foundational work of *Game Refinement Theory* and *Motion in Mind*, originating from the research of Professor Hiroyuki Iida, applying it to auctions as a model for economic games. The study focuses on the following key areas.

### 1.4.1 Game Refinement Theory and Motion in Mind Framework

To analyze the complexity of participant behaviors and non-economic motivations in auction environments, this study draws upon two key theoretical frameworks: *Game Refinement Theory (GR Theory)* and the *Motion in Mind* framework. Originally developed by Iida et al. [28], GR Theory provides a mathematical approach to understanding how uncertainty and game complexity impact player engagement and progression. It has been applied in various fields beyond gaming, such as commerce and education. The *Motion in Mind* framework, building on GR Theory, introduces concepts of game velocity and potential energy, emphasizing participants' desire to balance challenge with capability [2]. These frameworks are adapted here to quantify participant behavior and non-economic motivations in auction settings, offering new insights into the dynamics of economic games. A more detailed exploration of these frameworks and their application in economic games is provided in Chapter 2.

### 1.4.2 Game Theory and Auctions

Rooted in the pioneering work of *Von Neumann* and *Morgenstern* [8], game theory provides a foundational framework to model decision-making under uncertainty. Auctions naturally align with these principles, particularly concepts like expectation and utility, as participants must strategically manage uncertainty. This study builds on these foundations by analyzing how auction dynamics are shaped by both rational and irrational behaviors within this framework.

### 1.4.3 Auction Evolution as a Strategic Model

From ancient Babylon to contemporary platforms like *Sotheby's*, which includes online auctions, auctions have continuously evolved, not only as a means of resource allocation but also as a strategic model for understanding human decision-making [29]. Numerous Nobel Prize-winning economists, including William Vickrey, Robert Wilson, Paul Milgrom, Roger Myerson, and others, have extensively studied auctions for their structured, competitive environments, which offer rich data for observing a range of behaviors—from rational strategies to emotional bidding. Vickrey [7] introduced the concept of second-price auctions, foundational to incentive compatibility in auction design. Wilson's [30] work on common value auctions and asymmetric information advanced the theoretical understanding of auction behavior. Milgrom [31] expanded these theories to multi-item and combinatorial auctions, widely applied in spectrum auctions. Myerson's [32] contributions to mechanism design provided a rigorous framework for optimal auction design and incentive compatibility. These and other advancements have laid the groundwork for modern auction theory and its applications. This study further contributes by using auction data to refine the predictive capabilities of game models, examining how auction systems can balance sophistication and uncertainty to maximize engagement.

### 1.4.4 Game Utility and Non-Economic Utility in Auctions

The research integrates economic models with game refinement theory to explore *non-economic utility*—the motivations beyond financial gains that drive participants, such as status signaling and emotional engagement [7]. Using concepts like *game momentum* and *potential reinforcement energy* [33], this research delves into how auctions act as stages for conspicuous consumption, blending economic and non-economic incentives into a comprehensive analysis of market behavior.

### 1.4.5 Core Hypotheses

Building upon the theoretical foundations discussed, we propose two core hypotheses. These hypotheses directly address how auctions, as structured economic games, encompass both rational (economic) and irrational (non-economic) participant motivations, thereby providing insights into the broader research question regarding participant behavior in auction environments.

- **Auctions encompass both economic and non-economic utility**: Beyond economic utility, auctions offer *Non-economic utility*, which includes psychological and social satisfaction as key motivations for participants to engage in competitive bidding. These non-economic utilities are crucial for understanding why participants may bid beyond rational price points, driven by emotional or social factors.

- **Game Refinement Theory and the Motion in Mind framework help explain non-economic motivations**: These theoretical frameworks provide tools to understand how participants' behaviors during auctions are influenced not only by monetary incentives but also by emotional engagement and social recognition. By analyzing the decision-making process through the lens of these frameworks, this research aims to clarify how non-economic factors shape the dynamics of auctions.

### 1.4.6 Theoretical Expansion

This study not only contributes to the analysis of auctions as competitive economic games but also proposes expansions to existing theories by introducing models that capture the complexity of human behavior in auction environments. This includes the development of dynamic computational models for regularizing *irrational behaviors*, bridging the gap between mainstream economic theory and contemporary behavioral economics. By extending mainstream theories with new dynamic models, this research provides a fresh perspective on behavioral economics in structured competitive environments.

## 1.5 Auction Systems and Algorithms

In the era of AI, algorithms play an increasingly significant role in shaping economic transactions. Auctions are no exception. Algorithms can influence bidder behavior by optimizing bidding strategies, managing data, and providing real-time feedback. However, the interaction between humans and algorithms introduces new challenges, as participants may adapt to or influence these systems.

This research uses auctions as a subject to develop an analytical model that explores the dynamic relationship between algorithms and human behavior in auction settings. By integrating AI models with traditional economic theories, such as auction theory, this study seeks to create a framework for analyzing irrational yet consistent decision-making and behavior in economic games. The ultimate goal is to extend the model's application beyond auctions to encompass broader economic game theory scenarios.

## 1.6 Research Objectives and Significance

The primary objective of this study is to explore the intersection of auction theory, behavioral economics, and game theory, with a focus on the application of artificial intelligence (AI) in auction systems. Specifically, this research aims to:

1. Model and analyze the behaviors of auction participants through AI-driven simulations and game theory frameworks.

2. Examine how non-economic utilities, such as conspicuous consumption and social recognition, influence participant decisions in auction environments.

3. Optimize economic decision-making models and improve market predictions through the use of AI and game refinement methodologies.

4. Investigate the impact of algorithms on auction behavior and how AI can enhance the auction experience for both participants and organizers.

This interdisciplinary research contributes to several fields:

- **Economics and Behavioral Economics:** By introducing concepts like "game utility" and "non-economic game utility," this study offers new insights into irrational behaviors in economic games.

- **Game Theory and Auction Theory:** The application of game refinement theory and the motion in mind model to auction scenarios provides a novel approach to understanding and optimizing auction mechanisms.

- **Artificial Intelligence and Computer Science:** The integration of AI simulations with auction data highlights the potential for advanced computational methods to model participant behavior and optimize auction design.

- **Information Science and Data Analysis:** By using methodologies from game studies to label and quantify participant behavior, this study lays the foundation for future collaborations with large language models and other advanced AI systems.

## 1.7 Structure of the Dissertation

This dissertation aims to progressively explore the intersection of auction theory, behavioral economics, and game theory, with a focus on the application of artificial intelligence in auction systems. At the same time, it explores the feasibility of using algorithmic methods, such as computational complexity and game reward mechanism metrics, to inform quantitative research in the humanities.

### 1.7.1 Chapter 1: Introduction

This dissertation explores the intersection of game theory, auction theory, and behavioral economics, with a particular emphasis on the role of artificial intelligence (AI) in understanding irrational economic behavior in auction systems. By utilizing frameworks like Game Refinement Theory and Motion in Mind, this study aims to quantitatively assess how participants in auction environments behave and how their motivations, driven by non-economic factors, contribute to decision-making processes.

The research situates auctions not only as market mechanisms for resource allocation but also as platforms that incorporate elements of conspicuous consumption, social status, and entertainment value. This dual perspective is critical for understanding how auctions function as both competitive economic games and platforms for psychological and social engagement. The dissertation also examines the application of AI technologies to model participant behavior in digital auctions, further demonstrating the feasibility of using advanced computational methods to optimize auction design.

This study offers a comprehensive analysis that spans microeconomic and macroeconomic dimensions, from understanding individual bidding strategies to exploring how auction systems influence broader economic trends like urban development and population migration. By leveraging auction data and AI simulations, the research contributes to both the fields of game studies and economic modeling.

### 1.7.2 Chapter 2: Literature Review and Proposed Theory

This chapter provides a comprehensive literature review of auction theory, game theory, and their broad impacts on economics and psychology, with a particular focus on reviewing the applications of game refinement theory and the motion in mind model in highly competitive games (such as sports competitions) and casual entertainment games. It also introduces the theoretical framework developed in this dissertation. By analyzing casual entertainment games, highly competitive games, and economic market games, this chapter explores the applicability of game refinement theory and the motion in mind model in understanding participant behavior and further examines the feasibility of applying these models to economic games, such as auctions, to study irrational behavior.

First, this chapter reviews the theoretical foundations related to games and auctions, including the classification of games, auction types, play theory, game theory, auction theory, and gamification in economic markets. It demonstrates how game refinement theory and the motion in mind model, along with their extended frameworks, reveal the complex behaviors of participants in various gaming scenarios. Next, it discusses the strategic modeling methods used in casual entertainment games, highly competitive sports games, and e-sports, analyzing how these approaches help uncover decision-making patterns in different contexts. In particular, this section delves into how game refinement theory and the motion in mind model explain player behavior and strategy choices, laying the groundwork for exploring how gamification influences strategic choices in economic market games.

Subsequently, the chapter examines the application of these models in economic market games, particularly in the classic economic game of auctions. By analyzing specific cases of English and Dutch auctions, the chapter illustrates how the combination of game refinement theory and the motion in mind model can explain the irrational decisions made by participants and investigate the underlying motivations for these decisions, such as identity recognition and conspicuous consumption. Furthermore, the chapter introduces a new theoretical framework, the Gravitational Formula in the Mind model, demonstrating its applicability across different types of auctions and highlighting its importance in simulating auction strategies. Supported by actual auction data analysis, this chapter validates the adaptability of the model across different countries and cultural contexts, providing a foundation for future AI-based auction simulations.

Additionally, the chapter discusses the differences in perspectives among various participants in auctions, particularly the behavior of spectators. Based on psychological and physiological theories (such as the mirror neuron theory), the chapter explores how spectators experience the gamification of auctions through the motion in mind model and how this external perspective affects the overall auction experience. This analysis provides theoretical support for building an external perspective AI model.

Finally, the chapter expands the concept of "Non-Economic Game Utility" to the macroeconomic domain, particularly the impact of conspicuous consumption and identity recognition in auctions on urban development and population migration. Through the application of GIS technology and population data, the chapter demonstrates how these theories can be used to model urban development and population flows, exploring the feasibility of applying these models in macroeconomic contexts.

### 1.7.3 Chapter 3: Auction System and Motion in Mind

The objective of this chapter is to apply game refinement theory and the 'Motion in Mind' concept to analyze the psychological and social motivations influencing over 700 artworks auctioned by Christie's and Sotheby's from 2021 to 2023. This analysis reveals strong negative correlations between price deviations and auction velocity across different price segments, with correlation coefficients ranging from -0.7883 to -0.9187. This demonstrates the substantial impact of bidder motivations beyond mere economic transactions. Notably, the correlation weakens to -0.6144 in the highest price segment, indicating a shift towards more rational decision-making at higher financial stakes.

This research suggests that successful auctions must cater to a diverse array of bidder preferences, integrating economic, psychological, and social dimensions into their design. Strategic pricing and thorough market analysis are crucial in shaping bidder behavior and auction outcomes. Additionally, this study identifies the strategic use of attention in auctions as a significant factor that enhances social status and influences outcomes through conspicuous consumption. These insights indicate that effective auction strategies should leverage these dynamics to optimize engagement and success.

### 1.7.4 Chapter 4: Strategic Selection and Design of the First Auction Item: Analyzing Auction Dynamics through "Motion in Mind" and "Potential Reinforcement Energy"

This chapter explores the strategic importance of the first auction item in shaping auction dynamics, using the frameworks of "Motion in Mind" and "Potential Reinforcement Energy." Auctions, as a significant economic mechanism, are governed by specific rules that dictate participant behavior and decision-making processes. This research highlights how the initial item not only sets the pace for the auction but also serves as a psychological benchmark for bidders, influencing their engagement and motivation.

Through a comprehensive analysis of auction data from leading houses such as Christie's and Sotheby's, the chapter examines how initial items create a competitive environment that fosters higher bids and greater participant involvement. It discusses the interplay of psychological factors, such as the perceived value of items and bidders' emotional investments, demonstrating that auctions are driven by complex motivations beyond mere economic gains.

Additionally, the chapter introduces the Game Refinement Theory and the Game Progress Model to quantitatively assess bidder behavior, revealing insights into how the dynamics of the auction process can be manipulated to enhance participant experience. The findings underscore the necessity for auction houses to strategically design their auctions to maximize both financial outcomes and bidder satisfaction, paving the way for future innovations in auction practices.

### 1.7.5 Chapter 5: Enhancing Auction Experiences: Game Dynamics and customer experience (CX) Design

This chapter delves into the interplay between game dynamics and customer experience (CX) design within the context of auctions, leveraging over 700 artworks auctioned by Christie's and Sotheby's from 2021 to 2023. The focus is on understanding how psychological and social motivations, driven by game refinement theory and the 'Motion in Mind' concept, impact the dynamics of English auctions. This research reveals strong negative correlations between price deviations and auction velocity across different price segments, indicating significant shifts in bidder motivations and decision-making processes as financial stakes increase.

The study examines the strategic application of game design principles, such as the Serial Position Effect and the Peak-End Rule, to enhance participant engagement and satisfaction. By structuring auctions to create memorable start and end points, and by designing peak excitement moments, auction houses can significantly influence overall participant perceptions and their experiences. This analysis suggests that successful auctions require an integration of economic, psychological, and social dimensions into their design, with strategic pricing and market analysis being crucial for shaping bidder behavior and outcomes.

Moreover, the strategic use of attention in auctions emerges as a key factor. It not only enhances social status but also influences auction outcomes through conspicuous consumption. These findings underscore the need for auction designs that effectively leverage game dynamics to optimize engagement and satisfaction, offering profound insights into the non-economic utilities that significantly impact auction success.

### 1.7.6 Chapter 6: Rational Bidding Meets Emotional Viewing: The Landscape of English Auction Livestreams in the Age of Algorithms

This chapter focuses on analyzing how the game appeal of English auctions changes for viewers in the age of livestreaming. The concept of "conspicuous consumption," introduced by Thorstein Veblen in The Theory of the Leisure Class, is used to explore the psychological motivations behind participants displaying wealth and social status by purchasing items above their actual value. The study examines how auction livestreams provide conspicuous value for participants and auction houses, and how this value enhances the attractiveness of auctions.

In live auction settings, participants' behaviors are influenced by their awareness of being observed, a phenomenon that has been explored within social psychology. This dissertation examines the impact of audience presence on auction participant behavior, with a particular focus on how this awareness influences decision-making biases. Although the 'dramaturgical' aspects of self-presentation are not directly discussed here, the study explores behavioral responses that align with psychological concepts of social recognition and status signaling, especially in high-stakes auction scenarios.

The research includes several key steps.

**Psychological and Psychophysiological Foundations:** It elucidates the psychological basis of viewers watching auctions or games, particularly the complex neural mechanisms in the brain during sports viewing, including visual information processing, emotional resonance, and activation of social cognition networks.

**Theoretical Model Development:** From the viewers' perspective, it establishes models based on Game Refinement Theory and the Motion in Mind framework, analyzing how viewers perceive and engage with the auction process.

**Computer Simulation and Data Analysis:** Different bidding strategies in English auctions are simulated and analyzed, evaluating viewer perceptions and reactions to the auction process.

**Chapter Conclusions:** Based on theoretical analysis and actual data, conclusions are drawn regarding the effectiveness of auction livestreams in enhancing game appeal and the role of conspicuous consumption in this process. This chapter aims to reveal new characteristics of English auctions in the livestreaming era and their impact on viewer appeal, providing new perspectives and in-depth analysis for understanding modern auction formats.

### 1.7.7 Chapter 7: Conclusion

This final chapter summarizes the core contributions of this dissertation to auction theory, game theory, and computational modeling in information science. Utilizing Game Refinement Theory and the Motion in Mind framework with extensive auction data, a dual-perspective model (internal and external) was developed to analyze complex participant behaviors in auctions. The AI-driven simulation framework offers a structured approach to examine auction dynamics, emphasizing psychological factors like status signaling and conspicuous consumption in decision-making.

Future research directions include integrating phygital and augmented virtual environments to enhance auction model predictability and application in economic forecasting. Additionally, the study highlights the role of adaptive AI algorithms that dynamically respond to participant behavior and market conditions, advancing robust economic modeling. These insights support further innovation in digital auction design and provide a scientific basis for optimizing customer experiences in auction-like systems, live-streaming markets, and virtual transactions in the metaverse.

## 1.8 Chapter Conclusion

This introductory chapter has outlined the motivation, objectives, and significance of this dissertation. By exploring auctions through the lens of game theory, behavioral economics, and AI, this research aims to provide a deeper understanding of the complex factors driving participant behavior. Through AI-driven simulations and advanced theoretical models, the study will offer insights into optimizing auction systems for greater economic efficiency and participant satisfaction.

# Chapter 2

# Literature Review and Proposed Theory

## 2.1 Chapter Introduction

This chapter establishes the theoretical and computational foundations of this research, focusing on integrating game theory, Game Refinement Theory (GR Theory), and the analysis of irrational behaviors in economic games, specifically auctions. Drawing on principles from economics and information science, this research uses computational methods to model decision-making patterns encompassing both rational and non-rational behaviors.

We begin with a review of GR Theory and relevant economic literature, adapted here to quantify "game utility"—non-economic motivations beyond financial gain—that drive irrational behaviors in auction participants. By capturing participant engagement and behavioral variability, GR Theory bridges mainstream economic theory and real-world behaviors, facilitating simulations of both rational and irrational responses.

While traditional models such as the Von Neumann framework provide a solid theoretical foundation for rational decision-making processes, they often fail to capture the complex interplay between economic and non-economic utilities observed in competitive environments like auctions [8]. Although behavioral economics has begun addressing the influence of non-economic utilities, existing research largely relies on traditional statistical methods and psychological theories for qualitative analysis, lacking comprehensive quantitative exploration [34,35]. These limitations underscore the urgent need for more dynamic and interdisciplinary approaches.

This study bridges these gaps by integrating advanced analytical tools such as Game Refinement Theory and the Motion in Mind framework [2, 28]. These frameworks enable the quantitative characterization of non-economic utilities, such as emotional engagement and social recognition, which are often overlooked by traditional economic models. By combining these interdisciplinary tools, the study proposes a comprehensive model that not only captures rational behaviors but also delves into non-rational decision-making. This approach offers deeper insights into auction dynamics and the mechanisms underlying human decision-making under uncertainty.

This research further extends GR Theory and the "Motion in Mind" framework to auction environments, incorporating physical models to explore auction appeal and decision-making. The dual-perspective model, which analyzes both participant and observer behaviors, leverages interdisciplinary tools from AI and psychophysiology, providing a computational framework for examining gamified decision-making.

Finally, this chapter introduces "game utility" as a blend of economic and non-economic incentives, capturing motivations such as social recognition and competitive excitement. This approach offers a nuanced view of decision-making under uncertainty, beyond traditional statistical models. The AI-driven model developed here simulates and predicts irrational behaviors, offering insights for applications in digital market design and virtual environments.

### 2.1.1 Chapter Structure

The structure of this chapter is as follows:

- **Game Theory and Game Refinement Theory (GR Theory)**: This section provides a rigorous overview of foundational game theory concepts, including Nash equilibrium and strategic interactions, which serve as the basis for analyzing decision-making processes in economic models. Additionally, this section introduces Game Refinement Theory (GR Theory) and the "Motion in Mind" framework, as developed in recent studies, detailing their roles in quantifying the dynamics of participant engagement and behavioral variability. These frameworks are particularly relevant in capturing decision-making under uncertainty, and they are instrumental for modeling irrational behaviors and optimizing participant engagement through computational simulations.

- **Economic Literature Review**: This section synthesizes classical economic theories, such as utility theory and rational choice models, to establish the theoretical foundation of economic decision-making. Following this, the section on **Behavioral Economics** critically examines deviations from rational choice theory by introducing core concepts like prospect theory and cognitive biases, which address the limitations of traditional economic assumptions. The segment on **Conspicuous Consumption and Leisure Economics** further explores non-economic motivations, examining how social status and identity recognition influence consumer behavior, thereby creating an intersection between economic incentives and psychological factors in decision-making processes.

- **Game Utility and Non-Economic Game Utility**: This section discusses the transition from traditional economic utility to more complex notions of game utility and non-economic game utility, emphasizing the mathematical frameworks for quantifying these constructs. It elaborates on how non-economic incentives, such as competition-driven psychological rewards, contribute to decision variability in competitive environments. Additionally, this section introduces modeling techniques for capturing execution variability, highlighting the quantitative approaches used to analyze motivational dynamics in decision-making.

- **Auction Mechanisms and Types**: Here, we provide a comprehensive analysis of various auction mechanisms, including English and Dutch auctions, examining the mathematical and structural properties that distinguish these formats. This section delves into non-economic motivations—such as competitive psychology, social status signaling, and emotional engagement—that influence bidding behaviors and ultimately affect auction outcomes. By examining these dimensions, we establish a theoretical foundation for modeling auctions as a dynamic system with both economic and non-economic decision drivers.

- **Modeling Auctions Using Game Refinement Theory**: This section applies Game Refinement Theory and the "Motion in Mind" framework to develop a dual-perspective (internal and external perspective) model of auction dynamics. The model enables a quantitative analysis of both participant and observer behaviors, providing insights into complex interactions within auction environments. By modeling these behaviors, we identify key variables and patterns in bidding strategies and engagement metrics, which are then integrated into a computational framework to simulate auction scenarios under varying conditions of uncertainty.

- **Theoretical Integration and Chapter Summary**: In this final section, we synthesize the interdisciplinary frameworks within a unified research structure, establishing the foundation for theoretical and computational expansions in subsequent chapters. This synthesis highlights how non-economic utility metrics, modeled through Game Refinement Theory, provide new perspectives on economic decision-making under uncertainty, particularly in auction-based scenarios. This integration supports the development of AI-driven systems for simulating both rational and irrational participant behaviors, contributing to the broader objective of analyzing economic transactions through computational modeling.

## 2.2 Game Theory and Game Refinement Theory (GR Theory)

### 2.2.1 Game Theory

Game theory, pioneered by mathematician John von Neumann, is a mathematical framework used to study strategic decision-making among rational participants. Initially developed to model competitive situations in economics, it has since expanded to various fields, including biology, political science, and computer science.

Von Neumann's contributions to game theory, particularly in his 1944 work *Theory of Games and Economic Behavior*, co-authored with Oskar Morgenstern, laid the foundation for the formal study of decision-making processes in economic and social systems. Their work provided the axiomatic underpinnings of expected utility theory, building upon earlier concepts introduced by Daniel Bernoulli in 1738 [36]. The core idea behind game theory is that participants in these systems act as rational agents seeking to maximize their utility in competitive or cooperative scenarios.

As a key figure in both game theory and computer science—through the development of the von Neumann architecture—von Neumann established profound links between strategic thinking in economics and computational models. His pioneering work positioned games as powerful tools for simulating and understanding economic behaviors, thus bridging the gap between these fields. This connection has laid the groundwork for applying computational techniques and artificial intelligence to model and predict complex human behaviors in scenarios such as auctions and market dynamics.

#### 2.2.1.1 Von Neumann's Interdisciplinary Bridge: Axiomatization of Economics and Computer Science

Exploring the intersection of economics and computer science necessitates acknowledging the contributions of John von Neumann. He played a decisive role not only in the development of computer science but also in the formalization of economics through axiomatization. His research transcended traditional disciplinary boundaries, proposing methods to simulate and quantify complex behaviors in the real world, particularly in modeling the actions of real-world participants.

Game theory provides an ideal framework for observing and analyzing human behavior in real dilemmas, such as various competitive scenarios. In *Theory of Games and Economic Behavior*, von Neumann and Morgenstern formalized expected utility theory, marking a significant leap from axiomatic theory to practical application [8]. Prior to their work, economic quantification was primarily based on classical utility theory. They pioneered the use of axioms to establish a consistent and rational foundation for decision-making under uncertainty.

#### 2.2.1.2 Challenges and Limitations

Despite advances in physical and engineering sciences, quantification methods in social sciences often remain limited to basic statistical research. This gap presents both an opportunity and a necessity to develop new analytical frameworks. Games offer a natural bridge—not only because they effectively model complex economic and social behaviors but also because they serve as a key connection point between computer science and social sciences.

While von Neumann's framework has made foundational contributions by providing mathematical rigor for analyzing rational decision-making, its applicability to real-world scenarios involving complex human behaviors remains limited. Traditional economic models predominantly focus on rational utility maximization, often overlooking the nuanced motivations that drive participants in competitive settings like auctions. These models struggle to account for non-economic incentives such as social recognition, emotional engagement, and intrinsic enjoyment, which play a significant role in shaping decision-making.

By contrast, Game Refinement Theory and the Motion in Mind Framework offer an innovative approach that extends beyond economic optimization. These frameworks incorporate psychological and emotional dimensions of decision-making, enabling the quantification of engagement levels, the analysis of behavioral variability, and the prediction of participant actions in environments characterized by uncertainty and competition. This interdisciplinary approach provides a richer and more comprehensive perspective on auction dynamics, capturing both rational and non-rational behaviors.

As a graduate student in computer science, I've been particularly interested in exploring how computational techniques can be applied to the quantification of social sciences, especially in economics and finance. This interest stems not only from my background in finance but also from an understanding of the growing capabilities of computer science. The tools and methods provided by computer science, particularly in the era of big data and artificial intelligence, offer unprecedented opportunities for research in economics and finance. Applying these tools to social sciences is not merely an academic exploration but also an essential step in building interdisciplinary bridges.

#### 2.2.1.3 Transition to Irrational Economic Game Behavior

While classical economic theory often assumes rational decision-making based on the principle of utility maximization, behavioral economics has shown that human behavior frequently deviates from this ideal, especially in competitive or game-like scenarios [34]. Game theory, initially developed to model rational behavior, also provides a framework to explore the broader range of motivations that drive participants in economic games—many of which extend beyond purely financial rewards.

Participants may be influenced by psychological and social factors such as the desire for social recognition, status signaling, or the intrinsic pleasure of competition [37]. These irrational behaviors are integral to understanding the complexity of real-world decision-making. By examining both rational and irrational motivations in games, we gain a more comprehensive view of economic interactions.

Our research focuses specifically on these irrational behaviors in economic games. Although it may not always be possible to identify the exact reasons why participants engage in certain behaviors, it is clear that games serve purposes beyond mere financial gain. Individuals may participate to prove their worth to a group, reaffirm their sense of identity, or experience the inherent enjoyment of competition. This leads to the central question of my research: How does "non-economic game utility" influence participant behavior in economic games?

### 2.2.2 Game Refinement theory

Game Refinement Theory (GR Theory), introduced by Iida et al. [28] in 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 [2]. 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 [2, 33].

An important question arises: **Is Game Refinement Theory applicable to analyzing non-economic utility in economic contexts?** Before exploring whether and how GR Theory and its related theories can be utilized for this purpose, it is essential to review the fundamental concepts and principles of GR Theory and its associated theoretical frameworks.

With this foundation, we can better understand how GR Theory might be adapted to analyze non-economic factors in economic games.

#### 2.2.2.1 Information, Uncertainty, and Reward

To fully explain game-playing or the act of play as an information artifact, consider the intertwined nature of information, uncertainty, and rewards as a whole system. This involves revisiting three prominent components: game refinement theory, game progress model, and reinforcement theory.

GR Theory proposes a measure to identify the sophistication and uncertainty of a game's outcome based on the information science perspective, where it provides the utility to increase the game's attractiveness [38, 39]. An ideal game has a GR value within the range of $GR \in [0.07, 0.08]$ based on shared patterns of games found enjoyable for players of both beginner and advanced skill levels [40]. The formula for measuring GR differs depending on the type of game being analyzed (Equation 2.1).

$$GR = \frac{\sqrt{B}}{D} = \frac{\sqrt{2G}}{T} = \sqrt{a} \tag{2.1}$$

In this formula, $B$ represents the average branching factor, $D$ stands for game length, $G$ is the average number of successful scores, and $T$ is the average number of attempts per game. $\sqrt{a}$ symbolizes the acceleration of game velocity [41].

By applying the game progress model, we can quantify the decision-making process and perceptual experiences of players within a game. Players learn and perceive through pattern recognition, particularly when faced with unfamiliar abstract concepts, they tend to use analogies for prediction and understanding. In various types of games, players instinctively refer to the laws of physics for cognitive orientation, especially when the game mechanics align with these laws. For example, in chess-like games, players reduce uncertainty as the game progresses, where the amount of information gained at each step is represented by the variable $x(t)$, illustrating the relationship between information and time.

Meanwhile, the game progress model defines velocity ($v$) as the rate at which a player solves uncertainty, while mass ($m$) represents the difficulty of solving uncertainty. Velocity can be expressed as the winning or scoring rate for a game (Equation (2.2)). This model added a temporal development to the original GR theory, putting the concept of 'motion' to represent magnitude and diversity of experience based on the levels of uncertainty [33]. These concepts help to understand how quickly a player can progress and the level of difficulty in the game.

$$v = \frac{B}{2D} = \frac{G}{T} = 1 - m \tag{2.2}$$

The game's third component uses reinforcement theory, which is inspired by the notion of actions (reinforce, punish, and extinct) shaped by their consequences [42]. The variable-ratio reinforcement schedule ($VR(N)$) rewards players regularly after an unpredictable number of responses to maintain their interest [43]. As such, $N$ is associated with the average reward frequency ($1 < N \in \mathbb{R}$) and can be expressed as the inverse of the winning rate $v$ [44].

#### 2.2.2.2 Free Fall Motion in Mind

Solving the uncertainty of the outcome of a given thing, like a game, is akin to free-fall motion (uniformly accelerated motion) [2]. This implies that the progression is given by:

$$y = \frac{1}{2}a_0t^2 \tag{2.3}$$

where $a_0$ stands for the gravity in mind of the observer. On the other hand, a thing is characterized by its velocity as a random reward process. The progression is then given by a linear function:

$$y = vt \quad \text{where} \quad v = \frac{1}{N} \tag{2.4}$$

The cross point between the curve (2.3) and the line (2.4), say $(t_{12}, y_{12})$, is determined by:

$$y_{12} = y(t_{12}) = y\left(\frac{T}{N}\right) = \frac{T}{N^2} \tag{2.5}$$

where $T = \frac{2}{a_0}$ holds. We show, in Figure 2-1, an illustration of the process of solving the uncertainty of the outcome of a thing and the cross point between the straight line and the gravity in mind curve.

The notion of the potential reinforcement energy (PRE) is considered a measurement of the objectivity of the outcome of the thing under consideration (see Definition 1) [1]. People would expect to win the reward after $N$ times trials in a random reward event with variable ratio reinforcement schedule $VR(N)$. After multiple trials, it can be conjectured that a stochastic thing is transformed into a deterministic one.

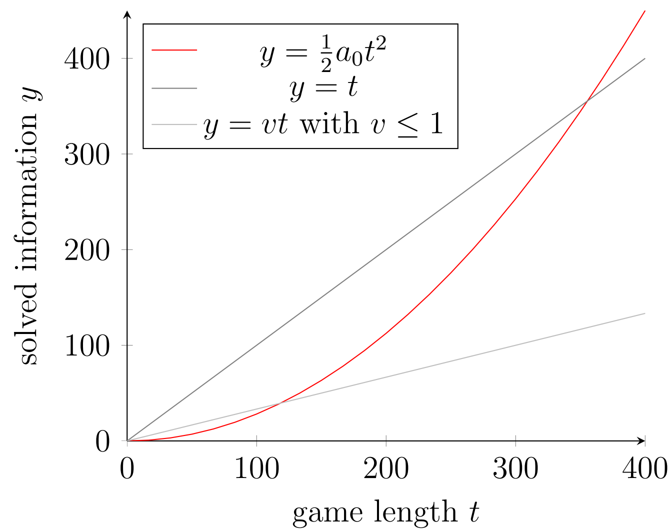



Figure 2-1: An illustration of the process of solving the uncertainty of the outcome of a thing: straight line and gravity-in-mind curve.

It is likely that a random reward event $VR(N)$ (where $N >> 1$) transforms into a deterministic event ($N = 1$) after $N^2$ times trials.

**Definition 1.** *Potential Reinforcement Energy (PRE) of a given thing, characterized by its velocity $v$ (hence $N = 1/v$), is defined as a function of the number of trials $\eta$, which is determined by:*

$$PRE(\eta) = \eta \cdot \frac{T}{N^2} \tag{2.6}$$

People may experience extraordinary feelings in space due to different levels of gravity (see Definition 2) [1]. This is because we are accustomed (comfort) to the standard gravity on Earth, and any variation can cause discomfort. The standard gravity in mind is represented by $a_0$, whereas any other degree of gravity (e.g., larger), denoted by $a$, may feel uncomfortable or extraordinary.

**Definition 2.** *The magnitude of extraordinary experience (MEE) is defined as the ratio of extraordinary gravity in mind over the standard one, determined by:*

$$MEE = \frac{a}{a_0} = \sqrt{N} \tag{2.7}$$

#### 2.2.2.3 Engagement Measure by Balancing Potential Reinforcement Energy (PRE) and Magnitude of Extraordinary Experience (MEE)

Figure 2-2 illustrates the potential reinforcement energy (PRE) and magnitude of extraordinary experience (MEE) with a focus on the two cross points [1]. It suggests that people would be highly engaged in a purely random reward event around the cross point between (2.4) with $\eta = N$ and (2.3). On the other hand, people would be highly engaged in a competitive event around the cross point between (2.4) with $\eta = 1$ and (2.3).

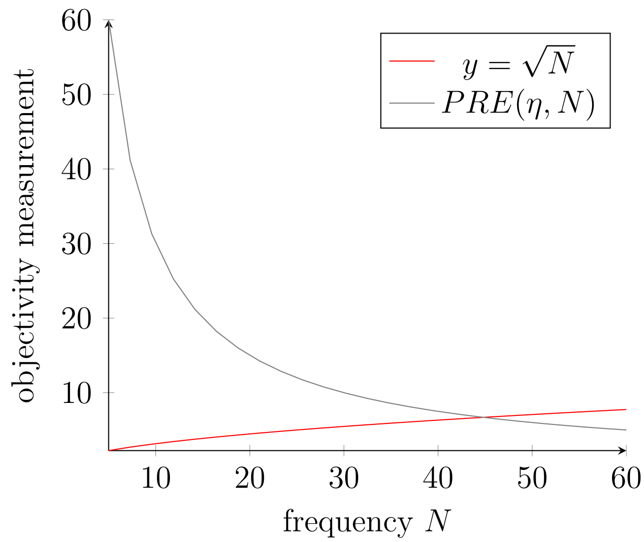



Figure 2-2: An illustration of potential reinforcement energy (PRE) and magnitude of extraordinary experience (MEE) [1].

Figure 2-2 indicates that an engagement point in the competitive context is around $N = 10$, whereas another engagement point in the purely random context is around $N = 55$. Incomplete information games with some stochastic aspects, like card games or Mahjong, are so engaged with relatively smaller $N \leq 10$ in the competitive context, rather than skill-based board games like chess with about $N \leq 5$.

After understanding the foundational concepts and recent developments in Game Refinement Theory, we are faced with two important questions. First, is this research method, traditionally used for studying games, appropriate for analyzing economic game scenarios? Second, which game scenarios allow us to relatively separate economic utility from non-economic utility, enabling a deeper analysis and discussion? To answer the first question, we need to address the second one. Specifically, to study game-related issues in economic contexts—particularly the challenging task of quantifying non-economic utility—we need to identify a domain with clear rules, well-defined game boundaries, and extensive prior research. Auctions fit this criterion perfectly.

We will now focus on a specific economic scenario, namely auctions, to demonstrate how these concepts can be applied and analyzed within this context.

## 2.3 Economic Literature Review

This section provides a brief review of relevant economic literature, focusing on conspicuous consumption, utility theory, and behavioral economics, and exploring how non-economic incentives influence decision-making. Compared to traditional economic models, these frameworks help us understand how decision-making under uncertainty is driven by social rewards such as status and identity. This study integrates insights from both information science and economics. For the sake of brevity and to emphasize information science, a comprehensive review of economic literature is provided in Appendix A, where readers can explore foundational economic concepts and their relevance to this research in greater detail.

**Classical Economics**

Classical economics, founded by Adam Smith and David Ricardo, emphasizes market self-regulation, where supply and demand determine prices [45]. Rational agents in competitive markets are assumed to achieve efficient resource allocation through transparent transactions [46]. However, information asymmetry and psychological factors in real-world scenarios often lead to deviations from ideal market models [47].

**Behavioral Economics**

Behavioral economics challenges the traditional assumption of rationality, revealing that individuals often make irrational decisions under conditions of risk. Prospect Theory, developed by Daniel Kahneman and Amos Tversky, shows that people tend to avoid losses more than they seek equivalent gains [48]. This field also uncovers various cognitive biases that affect decision-making, such as overconfidence and anchoring [49]. Behavioral economics integrates insights from psychology to provide a more realistic framework for analyzing market behavior [50].

**Leisure Economics**

Thorstein Veblen [25] introduced the concept of "conspicuous consumption," describing behavior where individuals display wealth through high spending to signal social status. Similarly, "conspicuous sympathy" enhances a donor's social prestige through public charitable acts [26].

### 2.3.1 The Dual Nature of Auctions: Convergence of Serious and Leisure Economics and Games

Conspicuous consumption is particularly evident in auctions, where the value of goods extends beyond their practical use to become symbols of social status. In auctions for luxury items, artworks, and rare collectibles, participants place high bids to demonstrate wealth and status, fulfilling psychological needs for 'face' or symbolic consumption [51]. In this context, auctions are not only economic transactions but also sources of psychological satisfaction that transcend economic value. Participants derive a sense of achievement and satisfaction from competition and winning. This pattern encourages specific bidding strategies, such as 'high-profile bidding' or 'frequent bidding,' to project indifference to cost. By utilizing insights from behavioral economics and game theory, the mechanisms behind conspicuous consumption can be further analyzed, models can be developed to quantify the intentions driving such consumption, and its impact on auction price dynamics can be explored. These analyses provide new perspectives for auction design and market prediction.

This dynamic underscores the unique interplay between "serious" and "leisure" aspects within auction environments [52]. Serious games are characterized by educational, training, or professional objectives, demanding substantial time, strategy, and resources from participants. Such games often follow strict rules and require significant skill and focus, as seen in simulations and competitive events. In contrast, leisure games emphasize relaxation and enjoyment, with simpler rules and lower barriers to participation, allowing users to engage without extensive commitment. Auctions often sit at the intersection of these types, particularly in leisure consumption contexts where the purpose and setting of bidding can vary. For instance, in cases like lotteries, small-stakes gambling, or casual auctions, participants engage primarily for enjoyment, showing minimal strategic investment. Here, auctions resemble leisure games, prioritizing entertainment and low-stakes engagement.

However, when these auctions involve higher stakes, complex strategies, or clearly defined financial goals, they resemble serious games. The bidding process in these cases involves strategic decision-making, risk management, and a deeper psychological investment, aligning more closely with serious games. Therefore, auctions can embody the characteristics of both serious and leisure games, depending on the participants' motivations, resources, and the level of strategic complexity involved.

The game-like nature of auctions, especially in the context of serious games and leisure economics, is a significant point of analysis. Within this framework, the bidding process in auctions can be seen as a strategic game. When participants are less sensitive to the deal price, or when the cost of acquiring a certain item does not significantly affect their normal life or career, the transaction may be viewed as a game [8]. This reduced sensitivity can arise from economic factors, such as higher financial capacity, or from the non-economic appeal of the items, such as rarity, emotional value, strategic motives, and purchasing power. English auctions, as a typical form of auction, represent an economic scenario where participants exhibit low sensitivity to the transaction price.

The interplay between economic goals and psychological drivers in auctions reveals a complex structure of incentives. This underscores the need for a deeper analysis of both economic and non-economic utility, each of which plays a unique role in shaping participants' bidding behaviors and strategic decisions.

## 2.4 Game Utility and Non-Economic Game Utility

To analyze the role of game stimuli in an economic context such as auctions, this research introduces the concepts of "game utility" and "non-economic game utility" to better capture the diverse motivations behind participants' decision-making in economic games. "Game utility" encompasses both economic and non-economic incentives, while "non-economic game utility" specifically refers to the non-monetary rewards participants derive from the game—such as the excitement of competition, the desire to win, and the need for social recognition. These non-economic factors often have a significant impact on participants' decisions. In some cases, the pursuit of status, prestige, or identity may surpass the motivation for monetary returns.

Quantifying the influence of non-economic stimuli remains a challenging issue. To address this, we propose a model that incorporates both economic and non-economic utilities into the decision-making framework.

### 2.4.1 Utility Theory and Uncertainty: From Classical Utility to Game Utility

Utility theory in traditional economics considers utility as the measure of satisfaction or benefit an individual derives from a decision [53]. Since Adam Smith [54] introduced the concept of the "invisible hand," utility theory has been developed to explain economic behaviors extending from individual decision-making to broader market activities. Daniel Bernoulli's [36] work introduced the concept of diminishing marginal utility, suggesting that the incremental happiness gained from wealth decreases as wealth grows. His model is expressed as (2.8).

$$U(x) = b \cdot \log(a + x) \tag{2.8}$$

where $U(x)$ denotes utility, $x$ represents wealth, $b$ is a constant, and $a$ is initial wealth. This model quantifies decision-making by applying the principle of diminishing marginal utility, laying the foundation for modern expected utility theory.

Jeremy Bentham and John Stuart Mill [55] further developed the concept of utility in the context of Utilitarianism, describing it as the ability of an action or object to produce benefits or prevent harm. They argued that decisions should aim to maximize overall happiness or benefit.

By the mid-19th century, economists like William Stanley Jevons [56], Carl Menger [57], and Léon Walras [58] incorporated the principle of diminishing marginal utility into mainstream economics to explain consumer demand and price formation. They proposed that consumers choose quantities of goods to consume under budget constraints to maximize utility [59]:

$$\text{Maximize: } U(x_1, x_2, \ldots, x_n) \tag{2.9}$$

$$\text{Subject to: } \sum_{i=1}^{n} p_i x_i \leq I \tag{2.10}$$

This can be optimized using the Lagrangian method:

$$\mathcal{L}(x_1, x_2, \ldots, x_n, \lambda) = U(x_1, x_2, \ldots, x_n) + \lambda \left( I - \sum_{i=1}^{n} p_i x_i \right) \tag{2.11}$$

At utility maximization, the following relationship holds for each good $i$:

$$\frac{MU_i}{p_i} = \lambda \tag{2.12}$$

In 1944, von Neumann and Morgenstern [8] formalized expected utility theory in *Theory of Games and Economic Behavior*, providing axiomatic foundations for decision-making under uncertainty. The mathematical expression for expected utility is:

$$U(x) = \sum_{i=1}^{n} p_i \cdot u(x_i) \tag{2.13}$$

where:

- $U(x)$ is the expected utility under uncertainty;
- $p_i$ represents the probability of each possible outcome $x_i$, satisfying $\sum_{i=1}^{n} p_i = 1$;
- $u(x_i)$ is the utility function associated with outcome $x_i$, reflecting the subjective value assigned to each outcome.

Expected utility theory posits that individuals maximize the expected utility of outcomes rather than their simple monetary value when faced with uncertainty. The theory is based on the von Neumann-Morgenstern (VNM) [60] axioms:

1. **Completeness**: For any two outcomes $L$ and $M$, individuals can express a preference or indifference:

$$L \succeq M \quad \text{or} \quad M \succeq L \tag{2.14}$$

2. **Transitivity**: Preferences are consistent across options. If $L \succeq M$ and $M \succeq N$, then:

$$L \succeq N \tag{2.15}$$

3. **Continuity**: If $L \preceq M \preceq N$, there exists a probability $p \in [0, 1]$ such that:

$$pL + (1 - p)N \sim M \tag{2.16}$$

4. **Independence**: Preferences remain unaffected by common outcomes. For any outcomes $L$, $M$, and $N$, and any $p \in [0, 1)$:

$$L \preceq N \quad \text{if and only if} \quad pL + (1 - p)M \preceq pN + (1 - p)M \tag{2.17}$$

Supported by these axioms, expected utility theory provides a rigorous mathematical foundation for decision-making under uncertainty, with significant implications in economics, game theory, psychology, and risk analysis.

Building on this foundation, the concept of "game utility" extends utility theory to encompass the complex motivations and behavioral characteristics that emerge in competitive contexts. It illustrates how utility theory has evolved from a classical economic framework into a more nuanced concept capable of explaining the driving forces behind actions within interactive environments.

### 2.4.2 Quantifying Non-Economic Game Utility

Measuring non-economic utility is challenging due to its intangible nature, much like how "dark matter" in physics is difficult to observe directly yet has a significant impact on the universe. Non-economic utility serves as the "dark matter" of game theory—it influences participant behavior despite being invisible within traditional economic models. Understanding these hidden influences enables a more comprehensive explanation of game behaviors and offers new insights into economic decision-making.

To conceptualize the relationship between total utility, economic utility, and non-economic utility, we can express the observed total utility $U$ as:

$$U = E + N + \delta \tag{2.18}$$

where:

- $U$ is the total observed utility derived from the game;
- $E$ is the quantifiable economic utility;
- $N$ is the non-economic utility;
- $\delta$ is a behavioral variability term, capturing the effects of participant skills, decision-making effectiveness, and execution reliability.

We show, in Figure 2-3, the components of total utility in a game.

By modeling $\delta$, we account for the variability in behavior resulting from individual characteristics and abilities. Under ideal conditions, where we assume no measure-

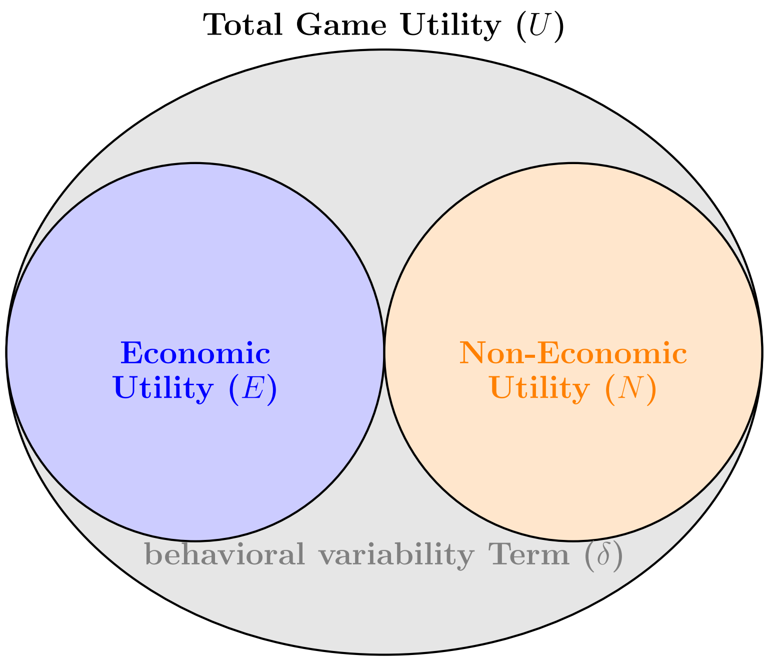



Figure 2-3: Components of total utility in a game

ment error $\epsilon = 0$ and ignore behavioral variability $\delta = 0$, total utility $U$ can be represented as:

$$U \approx E + N \tag{2.19}$$

or

$$U = E \cup N. \tag{2.20}$$

In this case, the additive form $U \approx E + N$ emphasizes the numerical summation of economic and non-economic utility, while the set form $U = E \cup N$ indicates that both components together constitute the total utility. We show, in Figure 2-4, the components of total game utility ($U$) with economic ($E$) and non-economic ($N$) utility. With this simplification, non-economic utility $N$ can be derived by subtracting economic utility from the observed total utility:

$$N = U - E. \tag{2.21}$$

or

$$N = U \setminus E. \tag{2.22}$$

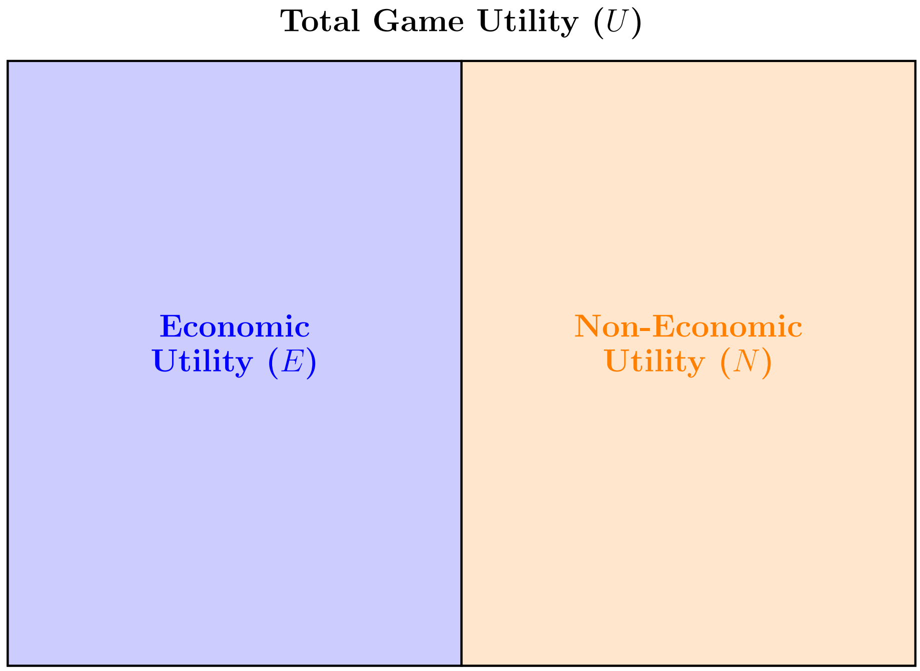



Figure 2-4: Components of Total Game Utility ($U$) with Economic ($E$) and Non-Economic ($N$) Utility, Assuming $\delta = 0$ and $\epsilon = 0$

To further quantify the non-economic utility $N$ and understand the behavioral variability term $\delta$, we consider the factors that contribute to deviations in participants' observed behaviors from theoretical predictions. Specifically, we recognize that participants' skills, luck value, decision-making effectiveness, and execution reliability play significant roles in these deviations.

#### 2.4.2.1 Mathematical Modeling of Execution Variability

To capture the impact of participants' skills and execution variability on the behavioral variability term $\delta$, we can develop a mathematical model that incorporates these human factors. By doing so, we enhance our utility model's ability to predict and explain game outcomes more accurately.

Let us consider the following parameters:

- Let $S_i$ represent the **skill level** of participant $i$, parameterized on a scale from 0 to 1, where 0 indicates no skill and 1 indicates perfect skill.

- Let $D_i$ represent the **decision-making effectiveness** of participant $i$, also scaled between 0 and 1.

- Let $V_i$ represent the **execution reliability** of participant $i$, defined as the probability that their intended action leads to the desired outcome.

We can model the error term $\delta_i$ for participant $i$ as a function of these parameters:

$$\delta_i = f(S_i, D_i, V_i) \tag{2.23}$$

where $f$ captures how skill level, decision effectiveness, and execution reliability contribute to deviations from expected utility.

Assuming that higher skill levels and decision-making effectiveness reduce the error term, while lower execution reliability increases it, we can define $\delta_i$ as follows:

$$\delta_i = (1 - S_i)\alpha + (1 - D_i)\beta + (1 - V_i)\gamma + \eta_i, \tag{2.24}$$

where:

- $\alpha, \beta, \gamma$ are weighting coefficients reflecting the relative importance of each factor.

- $\eta_i$ is a random error term accounting for unobserved factors, assumed to be normally distributed ($\eta_i \sim \mathcal{N}(0, \sigma^2)$).

Incorporating $\delta_i$ into our utility model, the non-economic utility for participant $i$ becomes:

$$N_i = U_i - E_i - \delta_i. \tag{2.25}$$

By modeling $\delta_i$ in this way, we can simulate how variations in skill levels and execution affect the total utility. This approach allows us to:

1. **Parameterize Skill Levels**: Assign quantitative values to participants' skills and decision-making abilities based on empirical data or assessments.

2. **Incorporate Probabilistic Elements**: Model execution reliability $V_i$ as a

probability, acknowledging that even skilled participants may experience unpredictable outcomes.

3. **Simulate Outcomes**: Use the model to simulate game outcomes under different scenarios, analyzing how changes in $S_i$, $D_i$, and $V_i$ impact the error term and overall utility.

**Example Simulation**

Suppose we have a participant with the following parameters:

- Skill level: $S_i = 0.8$
- Decision-making effectiveness: $D_i = 0.9$
- Execution reliability: $V_i = 0.85$

Assuming weighting coefficients $\alpha = 0.4$, $\beta = 0.3$, $\gamma = 0.3$, and $\eta_i$ negligible for simplicity, the error term $\delta_i$ is calculated as:

$$\begin{aligned} \delta_i &= (1 - S_i)\alpha + (1 - D_i)\beta + (1 - V_i)\gamma \\ &= (1 - 0.8)(0.4) + (1 - 0.9)(0.3) + (1 - 0.85)(0.3) \\ &= (0.2)(0.4) + (0.1)(0.3) + (0.15)(0.3) \\ &= 0.08 + 0.03 + 0.045 \\ &= 0.155 \end{aligned} \tag{2.26}$$

This behavioral variability term reflects the deviation in utility due to less-than-perfect skill, decision-making, and execution reliability. By comparing participants with different parameters, we can analyze how these factors influence the behavioral variability term and, consequently, the non-economic utility $N_i$.

However, both non-economic utility ($N$) and the behavioral variability term ( $\delta$) significantly influence participants' behavior in the game, causing deviations between their actual actions and their expected strategies. These deviations are reflected in the moves they make during the game. After the game concludes, if we construct a game tree, we can observe that these actions diverge from the expected outcomes. This discrepancy underscores the impact of non-economic factors and human variability on decision-making processes within competitive environments.

The mathematical modeling of execution variability provides a quantitative framework to incorporate human factors into game utility analysis. By parameterizing skill levels and introducing probabilistic elements, we enhance our understanding of the behavioral variability term $\delta$ and its impact on non-economic utility. This approach bridges the gap between theoretical models and real-world behaviors, offering a more comprehensive tool for analyzing economic games.

By integrating computational methods from computer science, such as machine learning algorithms and agent-based modeling, tools can be developed to better capture and analyze these non-economic factors [61]. To further quantify the attractiveness and engagement levels influenced by non-economic utility in economic games, the "Game Refinement theory" is employed, a framework traditionally applied to board games, video games, and sports competitions. Since this research concentrates on non-economic utility, Chapters 3 through 5 of this thesis assume that the behavioral variability term is zero, i.e., $\delta = 0$ . In Chapter 6, the behavioral variability term $\delta$ is incorporated and categorized through auction simulation algorithms. These algorithms take into account factors such as the AI bidders' information gathering capabilities, their beliefs about other participants, and the degree to which they modify their beliefs upon receiving new information.

## 2.5 Auction

Selecting an economic environment suitable for quantitative experimental research on non-economic utility or game utility is a challenging task. Many economic activities involve complex variables and uncertainties, making it difficult to separate economic utility from non-economic utility. However, auctions, as a form of economic transaction, have clear rules, well-defined game boundaries, and extensive prior research, making them an ideal scenario for our in-depth analysis and discussion.

Auctions involve not only the economic decisions of participants but also elements of competition, psychological strategy, and emotional factors, which are key components of non-economic utility. By studying auctions, we can relatively independently examine the impact of non-economic utility on participant behavior, thereby gaining a deeper understanding of the complex motivations in economic games.

Next, we will delve into the characteristics of auctions, analyzing why they serve as an ideal platform for studying non-economic game utility. We will also explore how to apply Game Refinement Theory and other related theories to evaluate the non-economic utility in auctions, providing a solid theoretical foundation for our research.

### 2.5.1 Auction Theory and its Development

Auction theory, an integral branch of economics and game theory [7], examines the behaviors and strategies of buyers and sellers in auction markets, commonly applied in sectors like art, real estate, stocks, and telecommunications [31]. The theoretical foundation of this concept, proposed by William Vickrey [7] and building upon the equilibrium theory initially established by John Nash [62], has evolved through contributions from Paul Milgrom and Robert Wilson [31], whose innovations in auction formats and market design have significantly advanced the field [14]. Their work emphasizes the role of game theory in analyzing strategic interactions and incomplete information in auctions.

Milgrom and Wilson's research on auction mechanisms has led to new auction formats and practical applications, impacting industries such as telecommunications and natural resources [9]. Their contributions continue to inform both theoretical and applied research in auction theory (see Appendix C for an expanded discussion).

### 2.5.2 Characteristics of Auctions

Understanding the theoretical foundations of auction theory allows us to appreciate the unique characteristics of auctions that make them ideal for analyzing non-economic utility through Game Refinement Theory. Auctions are structured environments where participants engage in competitive bidding under specific rules. This structure makes them particularly suitable for examining both economic and non-economic utilities.

Below we show five key characteristics that highlight the suitability of auctions for this purpose. **Clear Rules and Defined Boundaries**

Auctions are governed by a precise set of rules that delineate the actions participants can take, the conditions for winning, and the manner in which items are distributed among bidders. These rules are transparent and uniform, ensuring that all participants understand the auction process. For example, in an English auction, the rule is that each bid must be higher than the previous one, with the auction ending only when no higher bids are made. Such clarity allows researchers to model and predict participant behaviors within these well-defined parameters, minimizing external variability and facilitating rigorous analysis. This structure also means that data collected from auction scenarios can be more reliably interpreted, as the consistent rules reduce the influence of confounding variables.

**Strategic Interaction**

In auctions, participants are not isolated decision-makers but must continuously adapt their strategies in response to other bidders. This creates a dynamic interaction where bidders must consider not only their own valuations but also predict the actions and intentions of competitors. For instance, in sealed-bid auctions, bidders often try to gauge what others might bid, aiming to submit an optimal bid that maximizes their chance of winning while minimizing overpayment. This strategic interplay is central to game theory and allows auctions to function as microcosms of competitive behavior. Studying these interactions provides insight into decision-making processes that extend beyond mere monetary considerations, as participants might adjust their strategies to outmaneuver or outbid competitors due to non-economic motivations like pride or rivalry.

### Uncertainty and Risk

A fundamental aspect of auctions is the inherent uncertainty about other participants' actions and valuations, which introduces an element of risk. Bidders are typically unaware of the maximum amounts others are willing to pay, forcing them to make decisions under conditions of incomplete information. This uncertainty is compounded by the fact that bids are often irrevocable, meaning that a participant cannot retract their bid if they later determine they overpaid. The risk of overpaying—commonly referred to as the "winner's curse"—adds a psychological dimension to auctions, as participants must balance their desire to win with the potential regret of overvaluation. This aspect of risk allows researchers to study how individuals weigh economic utility (getting a good deal) against non-economic factors such as the thrill of competition and the fear of losing, both of which can drive higher bidding behavior.

### Competition and Social Factors

The competitive nature of auctions inherently evokes emotional responses among participants. The prospect of winning or losing against others, particularly in public auctions, can amplify feelings of excitement, tension, and competitiveness. For example, in high-profile auctions, the visibility of the bidding process can lead participants to act not only out of economic self-interest but also to project an image of status and wealth. This social dimension is exemplified in art auctions, where individuals might bid on a prestigious artwork partly to signal their cultural capital or social standing. Such social dynamics are integral to understanding non-economic utility, as participants derive satisfaction not just from acquiring items but from the social recognition and prestige associated with winning. These factors contribute to auction environments being highly suitable for studying how non-economic motivations impact economic decisions.

### Economic and Non-Economic Incentives

While auctions primarily serve as mechanisms for resource allocation, they also provide a platform for individuals to pursue various non-economic incentives. Economic motivations—such as obtaining a desired item at a favorable price—are often the primary drivers of participation. However, non-economic incentives frequently play an equally significant role. For instance, bidders may derive enjoyment from the excitement of the bidding process itself or feel a sense of accomplishment from successfully outbidding rivals. Social recognition, status, and even the intrinsic pleasure of competing are additional non-economic factors that influence participant behavior. These diverse motivations allow researchers to study auctions as arenas where economic and non-economic utilities intersect, providing insights into the complex drivers of human behavior. By examining how these incentives interact, researchers can better understand the nuanced motivations that underpin economic transactions in auction settings.

### 2.5.3 Auction Rules and Fundamental Concepts

Auctions are competitive resource allocation mechanisms designed to determine the market value of goods or services through open bidding. The core of an auction lies in its well-defined rules, which not only dictate how participants bid but also influence the dynamics and outcomes of the auction. The primary auction rules include the following key aspects:

#### 2.5.3.1 Types of Auctions

Auctions are categorized based on their rules and bidding formats. Common types include English auctions, Dutch auctions, sealed-bid auctions, and second-price auctions. English auctions follow an ascending price format, where participants progressively increase their bids until no higher bids are made, while Dutch auctions start with a high price that decreases until a buyer accepts the current price.

#### 2.5.3.2 Starting Price

The starting price is the initial bid set by the auctioneer for the first round of bidding. It is typically determined based on market expectations and the estimated value of the item. The level of the starting price directly impacts the bidding interest of participants; a price set too high may deter bidders, whereas a price set too low could limit the final price potential.

#### 2.5.3.3 Bid Increments and Restrictions

Bid increments represent the minimum increase required for each round of bidding, ensuring a smooth and fair bidding process. Some auctions also impose maximum or minimum bid restrictions to mitigate risks of abnormal behavior or excessive competition.

#### 2.5.3.4 Impact of Rules on Non-Economic Utility

Auction rules influence not only the economic utility (e.g., price and profit) but also the non-economic utility (e.g., social recognition, status signaling, and psychological satisfaction) of participants. For instance, a higher starting price can create an impression of exclusivity, attracting participants motivated by conspicuous consumption, while competitive bidding increments enhance the emotional engagement and excitement of the process. Similarly, a longer active phase can provide more time for strategic decision-making, fostering a sense of achievement and satisfaction when winning. For example, art auctions often use elevated starting prices and carefully timed bid increments to amplify participants' desire for social recognition and prestige, as highlighted in Veblen's theory of conspicuous consumption [25]. This interplay between economic and non-economic factors is critical for understanding auction dynamics.

### 2.5.4 Auction Types and Strategic Variations

Auction types exhibit significant variations, particularly in terms of information disclosure and auction format, which collectively shape participant behavior and strategic approaches [14]. Auction theory encompasses multiple formats, including English auctions (ascending order), Dutch auctions (descending order), first-price sealed-bid auctions, and second-price sealed-bid auctions [7]. Each format creates distinct strategic environments that influence the decision-making dynamics of sellers and buyers.

The structural composition of an auction market—whether a single-item auction involving one seller and multiple buyers or a multi-item auction with numerous participants—also plays a substantial role in shaping bidding strategies. For instance, in single-item auctions, the seller's selection of a winning bid relies on direct competition among potential buyers, while multi-item auctions require participants to consider the actions and potential responses of other buyers and sellers in a more complex and interdependent decision-making framework.

By analyzing these variations in format and participant structure, auction theory offers valuable insights into the strategic interactions of market participants, providing a foundation for optimizing decision-making processes and achieving efficient and desirable market outcomes [7, 62].

For an in-depth examination of specific auction types, their underlying mechanisms, and their implications for non-economic motivations, refer to Appendix C. To distinguish between the descriptive terms used for auction rules and the terminology applied in game-theoretic modeling, this study adopts "initial price" and "final price' instead of colloquial terms like "starting price" and "closing price." This differentiation aligns with the academic nature of the research and ensures consistency in the analysis.

### 2.5.5 Connecting Auction Characteristics to Research Objectives

The above auction types underscore the significance of studying both economic and non-economic incentives within auction environments. Auctions, with their structured and rule-based nature, align closely with game theory principles, allowing for the quantification of economic decisions. At the same time, elements of competition, uncertainty, and social interaction create a fertile ground for analyzing non-economic motivations. This combination makes auctions a valuable model for exploring broader questions of how non-economic utility influences economic decision-making.

Given the diversity of auction types, each format presents unique characteristics worthy of study. However, since this research focuses on the role of non-economic utility, it is essential to choose auction types that facilitate the observation and measurement of participants' behaviors, including those of potential bidders who may simply be observing. Therefore, this study primarily examines open outcry auctions, specifically the English auction and Dutch auction. English auctions, commonly involving luxury items and art, enable the clear distinction between economic and non-economic utilities. Dutch auctions, often used for time-sensitive goods, such as flowers, fish, bring a unique dynamic due to their rapid pace. Consequently, this research emphasizes English auctions for initial analysis, with plans to extend to Dutch auctions to explore varying impacts on non-economic motivations.

From auction theory, we understand that auctions represent a Bayesian equilibrium game and can be viewed as a zero-sum game between buyers and sellers, excluding intermediaries like auction houses or proxy bidders. Participants have access to both public information (such as auction rules and past prices) and private information unique to each bidder. The resulting information asymmetry and decision-making under uncertainty are distinguishing features of auctions. Additionally, auctions provide the option to "stop bidding," allowing a participant to withdraw without financial loss. Winning an auction at a price higher than the item's true value introduces the risk of the winner's curse, underscoring the role of non-economic motivations in decision-making. The decision models and algorithms developed through auction simulations can be adapted to analyze other economic scenarios with similar game structures, contributing valuable insights into the interplay of economic and non-economic incentives in complex environments.

## 2.6 Modeling Auctions Using Game Refinement Theory

This section applies Game Refinement Theory (GR Theory) and the “Motion in Mind” framework to analyze auction systems from both participant and observer perspectives, revealing how auction dynamics impact decision-making processes. GR Theory and the “Motion in Mind” framework define game progression velocity (game momentum) to quantify players’ engagement motives, while potential energy ($\vec{E_p}$) captures participants’ expectations, balancing success rates with challenges to shape the game experience.

In auction modeling, auctions are viewed as leisure games where price transitions and bidding strategies reflect the influence of non-price factors (e.g., rarity, emotional value). By standardizing the changes between initial and final prices, competitive behavior is analyzed. Furthermore, by employing the physical analogy of the “restricted three-body problem,” core auction items are considered as “gravitational centers” that influence other bids. The “Gravitational Formula in the Mind” is then utilized to quantify these dynamic relationships.

From the observer’s perspective, GR Theory is employed to analyze the randomness of auctions and key decision points (participation, bidding, and withdrawal). By integrating neurophysiological research, this approach provides insight into risk decision-making and the spectator experience. Ultimately, an AI-driven dual-model system is used to predict rational and irrational decision-making in auctions. The internal model assesses participant behavior, while the external model evaluates observer engagement, enhancing AI’s application in economic scenarios and virtual markets.

### 2.6.1 Auction System and its Analysis for Participant's Perspective

This section applies Game Refinement Theory (GR Theory) and the 'Motion in Mind' framework to analyze the behavior of participants in auction systems. By integrating economic modeling with GR Theory, the Motion in Mind framework, and behavioral economics, we aim to provide insights into how participants perceive auction dynamics and how these dynamics influence their decision-making processes.

#### 2.6.1.1 Principle Review

Building upon the Game Refinement Theory, the "Motion in Mind" framework further delves into the dynamics of gaming from a player's cognitive perspective. This concept revolves around the idea that a game's progression is fundamentally influenced by the rate of successful information acquisition. Here, the velocity of the game, denoted by $v$, signifies the player's success rate in overcoming uncertainties or challenges.

Interestingly, the perceived quality of the game inversely correlates with its velocity, based on a zero-sum game payoff function. This is expressed as $m = 1 - v$, where a velocity of $v = \frac{1}{2}$ indicates equal probabilities of winning and losing [2]. This concept underscores the intricate balance between the rate of success and the game's inherent challenges, impacting player engagement and perception of the game.

$$\vec{p} = m \cdot v = (1 - v) \cdot v \tag{2.27}$$

Moreover, the framework introduces the concept of game momentum ($\vec{p}$), which is a measure of the likelihood that players will continue to engage and focus on the game. This momentum is influenced by the players' tendency to persist in playing, even as the difficulty level fluctuates. Essentially, $\vec{p}$ represents the momentary trend based on the current game speed, akin to the momentum of a moving object in physics. It reflects the effort required to change the game state and the players' propensity to maintain their engagement and focus, especially when their success rate remains constant. Thus, a high value of $\vec{p}$ suggests a player's optimal effort in balancing challenges and abilities, thereby maximizing engagement with the game.

Meanwhile, the concept of potential energy in this framework, denoted as $E_p$, relates to the energy stored in the game system at its initial state. This energy is analogous to the players' expectations of achieving a particular game state and is quantified in the following equation:

$$E_p = 2mv^2 \tag{2.28}$$

The value of $E_p$ is dependent on winning rates and varies based on the player's energy and expectations. It signifies the amount of game information necessary for players to progress and is associated with their desire to complete the game and the level of comfort experienced in winning. This concept of potential energy provides game designers with a tool to assess the stability and complexity of a game, enhancing the player's experience and engagement.

In summary, the "Motion in Mind" framework complements the Game Refinement Theory by offering a deeper understanding of the psychological and cognitive elements at play, highlighting how players interact with and perceive the game dynamics.

#### 2.6.1.2 Modeling Individual Auction Items

This section discusses the auction system and its analysis through the lens of GR theory and the motion-in-mind framework, highlighting the understanding of information dynamics, play experience, and attraction. We explore the relationship between auctions and games, especially in the context of leisure games, where the auction bidding process is fundamentally a strategic game. Auctions are considered leisurely games when participants are less sensitive to final prices, possibly due to non-price factors (like rarity, emotional value, or strategic purposes) and purchasing power.

In the auction process, be it English or Dutch auctions, the price transitions from an initial price $I_{\text{price}}$ to a final selling price $F_{\text{price}}$. The relative magnitude of this price change is evaluated by comparing the difference between these prices. Consequently, based on GR theory and the game progress model, we define the variable $m$ to measure the difficulty of the relative price change process from the initial to the final price, where its value ranges from 0 to 1, indicating mild to intense competition. The auction's velocity and frequency are then defined as follows:

$$m = \frac{|F_{\text{Price}} - I_{\text{Price}}|}{\max(F_{\text{Price}}, I_{\text{Price}})} \quad \text{where} \quad 0 \leq m \leq 1 \tag{2.29}$$

$$v = 1 - m = \frac{\max(F_{\text{Price}}, I_{\text{Price}})}{\min(F_{\text{Price}}, I_{\text{Price}})} \tag{2.30}$$

$$N = \frac{1}{v} = \frac{\min(F_{\text{Price}}, I_{\text{Price}})}{\max(F_{\text{Price}}, I_{\text{Price}})} \tag{2.31}$$

Through these formulas, we standardize the assessment of the magnitude and efficiency of price changes, further analyzing decision-making behavior patterns in auction markets, considering non-economic utilities.

Two important clarifications are necessary. First, although different auction markets use different currencies, this study focuses on the impact of the numerical differences represented by prices on auction participants and thus does not convert auction amounts to a uniform currency value. This approach allows for a purer analysis of the psychological and strategic impacts of price changes. Second, considering that the bidding prices in the art auction market are typically high for each bid increment, we adopt a method that conforms to the human brain's habitual processing of information: by dividing both the initial and final prices by the minimum bid increment. This calculation not only helps simulate the sensation of acceleration in auctions but also reflects the psychological state and strategic choices of participants during competition.

$$G_{\text{Auction}} = \frac{\min(F_{\text{Price}}, I_{\text{Price}})}{\Delta p} \tag{2.32}$$

$$T_{\text{Auction}} = \frac{\max(F_{\text{Price}}, I_{\text{Price}})}{\Delta p} \tag{2.33}$$

$$GR = \frac{\sqrt{G}}{T} = \frac{\sqrt{2^{\frac{\min(F_{\text{Price}}, I_{\text{Price}})}{\Delta p}}}}{\frac{\max(F_{\text{Price}}, I_{\text{Price}})}{\Delta p}} \tag{2.34}$$

#### 2.6.1.3 Modeling a Set of Games

Through the above analysis of auction dynamics using physical analogies, we have gained a preliminary understanding of how the Game Refinement Theory and the Motion in Mind Framework can be applied to auctions as a unique economic game. However, real-world auctions rarely involve a single item; instead, auction houses typically curate groups of 20 to 40 items collected throughout the year and conduct auctions during specific seasons. This is particularly evident in prestigious auction houses like Sotheby's and Christie's during their major Spring and Autumn auctions [63]. In these scenarios, participants are not engaging with isolated auction games but rather with a series of interconnected games.

Each auction forms an independent game, yet they exert mutual influence. Notably, core items often attract significant attention, impacting the dynamics of the entire auction session. Even participants who are not directly bidding on the core items are often influenced by their presence. This phenomenon is analogous to the gravitational effects observed in astrophysics, where core items (high-mass objects) exert a significant influence on the behavior of participants (negligible-mass objects). These core items not only shape participants' decision-making processes in relation to themselves but also affect their engagement in auctions of other items with comparatively lower value. This cascading effect underscores the interconnected dynamics within the auction environment. To further refine this concept, we will employ dynamic pricing models, enabling precise analysis of price fluctuations and participant decisions. This approach allows us to quantify interactions within auctions and provides data-driven insights for optimizing auction design and strategy.

**The Restricted Three-Body Problem and Gravitational Formulas in the Mind**

Based on our study of real auction data, we have observed significant changes in the auction speed surrounding core auction items, sometimes even leading to the neglect of items without sufficient bids. This phenomenon closely relates to certain astronomical phenomena. This observation inspired us to consider whether there exists a dynamic similar to gravity in physics within the auction process, where certain core auction items exert a "gravitational" influence on the performance of surrounding auction items in terms of auction speed. To further explore this conjecture, we propose a unique analytical framework inspired by the "restricted three-body problem" in physics, where two large mass bodies significantly affect a third body of negligible mass. In our model, the two "massive bodies" symbolize the most attention-garnering auction items, while the "negligible mass body" represents auction participants, whose behavior is significantly influenced by the core auction items.

Figure 2-5: The Three-Body Problem.[1]

In the context of auctions, participants often make decisions revolving around one or two core items, similar to how a small body is affected by the gravitational forces

[1]This figure was created by the author.
[2]This figure was created by the author.

Figure 2-6: The Restricted Three-Body Problem.[2]

of two large bodies, making the application of the model intuitively reasonable. Using this model as a framework to analyze auction dynamics has several advantages:

**Moderate Complexity**: Compared to the binary star problem, the restricted three-body problem more precisely depicts the unilateral influence of one or more bodies on a smaller body, which aligns more closely with the reality of how core auction items influence participants in auctions.

**Direct Analogy**: In the auction environment, participants often make decisions revolving around one or two core items, similar to how a small body is affected by the gravitational forces of two large bodies, making the application of the model intuitively reasonable.

**Theoretical Extensibility**: Employing this physical model not only provides a new perspective for analyzing known data but may also reveal patterns and relationships in auction behaviors that have not been observed before, offering new possibilities for theoretical and practical development.

Additionally, the model considers how participants form their own unique "game mass" through strategic decision-making, information processing, and psychological factors, reflecting their agency and market impact during the auction process. Through this approach, we hope to explore and understand more deeply the competitive dynamics in auctions, particularly how high-value auction items shape the entire auction process.

By applying the framework of the "restricted three-body value problem," we can not only vividly describe the interactions in the bidding process but also delve deeper into how core auction items influence participants' decisions and bidding behavior through their "game mass." This analytical framework helps us identify which auction items have significant market impact and predict how they may alter the overall dynamics of the auction.

Next, we will concretize these theoretical perspectives by introducing the "Gravitational Formula in the Mind," a quantitative method aimed at simulating and analyzing the dynamic interactions between core auction items and between items and participants. This method draws from the core principles of the universal law of gravitation, using "mass" and "distance" as variables to explore how core auction items influence each other during the bidding process.

### The Restricted Three-Body Problem

The concept of the restricted three-body problem is a metaphor for the dynamics observed in auctions. We assume that the auction process is a game where participants (players/bidders) go through one auction item after another, each auction process containing a well-defined game process. This makes the process akin to a small spacecraft flying past one celestial body after another. We do not dismiss that each participant's interest in items, capital amount, and other factors may result in different game masses. However, because the game mass inherent to participants is negligible compared to the game mass generated by the auction process of items, they can be considered as bodies of negligible game mass. The game process of two auction items (the "large mass bodies") exerts a significant gravitational influence on the game behavior of participants (the "negligible mass bodies"). Similarly, the game process of auction items with lighter game mass surrounding the core auction items is influenced not only by the game mass of the core auction items but also by the game mass of the current auction item. By observing the game velocity of these auction items at different distances, we hope to understand the influence of core auction items on other auction items. Furthermore, we aim to gain insight into the changes in the attractiveness of auction items felt by participants throughout the auction process.

Having outlined the metaphorical framework of the auction process through the lens of the restricted three-body problem, we now turn our focus towards a more concrete and quantifiable approach to understanding the gravitational forces at play within auctions. The necessity for a simplified yet powerful model to capture the essence of auction dynamics leads us to consider the principles of gravitational interaction not just as a metaphor, but as a foundational element of our analytical toolkit. Thus, we introduce the concept of "Gravitational Formula in the Mind," which draws directly from the universal law of gravitation, adapting its core principles to the context of auction dynamics. This approach allows us to move beyond the qualitative analysis, offering a quantitative method to examine the influences and interactions that govern the auction process.

**Gravitational Formula in the Mind**

Considering the characteristics of auction dynamics and the preliminary stage of our research, we chose to employ a simplified model analogous to the universal law of gravitation as our analytical tool. This decision is based on several key considerations:

**Intuitiveness and Simplicity**: The universal law of gravitation provides an intuitive and relatively simple way to describe the interaction between two objects, making the model not only easy to understand but also to implement. In the context of auctions, this model allows us to use "mass" (the attractiveness of the auction item) and "distance" (the relationship between the item and the participants) as key variables to explore the influence of core auction items on the dynamics of the auction.

**Scalability and Adaptability**: Although the universal gravitation model is relatively simple in representation, it offers enough flexibility to adapt to various auction scenarios and dynamics. The model can be adjusted based on the availability of data and specific research needs, such as introducing additional variables or modifying the influence weights of existing variables.

**Bridging Theory and Empiricism**: By applying concepts from physics to the field of economics, our model not only provides a new perspective for auction theory but may also uncover patterns and relationships in empirical data that have not been noticed before. This interdisciplinary approach fosters theoretical innovation and lays the groundwork for further empirical research.

Although general relativity offers a more complex and comprehensive framework for describing gravitational effects, considering the specific context and objectives of auction research, we believe that adopting the universal gravitation model is a more reasonable choice. This approach enables us to effectively capture and analyze the core dynamics within auctions, while maintaining manageability and clarity of analysis.

To concretize this framework, we adopt the universal law of gravitation as the mathematical description of the interactions between core auction items as well as between items and participants. The formula is as follows:

$$\mathcal{F} = \mathcal{G}\frac{m_1 m_i}{r_i^2} \tag{2.35}$$

In our model, $\mathcal{F}$ represents the gravitational force between two auction items, or the interaction force between an item and a participant; $\mathcal{G}$ is the gravitational constant, which in our model can be considered as an adjustment factor for the auction environment; $m_1$ and $m_i$ represent the "game mass" of two entities. In the context of auctions, $m_1$ specifically refers to the uncertainty a participant must overcome to acquire the core auction item, i.e., the "game mass" of the core auction item. Meanwhile, $m_i$ refers to the uncertainty a participant must overcome to acquire other auction items, such as auction item $i$, i.e., the "game mass" of auction item $i$. $r$ represents the distance between the two, which in our model, signifies the gap between the order of appearance of two lots within the same auction.

$$r_i(\mathcal{F}) = \sqrt{\frac{\mathcal{G} m_1 m_i}{\mathcal{F}}} \tag{2.36}$$

By employing the aforementioned formula, our goal is to quantitatively assess the dynamic interactions between core auction items and other items during the auction process, thereby offering an effective tool for forecasting and elucidating changes in auction behavior. This approach extends our analysis beyond treating games as isolated single interactions, broadening the perspective to encompass a designed set of interrelated games.

### 2.6.2 Model for Observer's Perspective

When observing an English auction from a non-participant's perspective, such as a researcher, auction house, or game designer, we cannot determine each participant's exact thought process when making a bid or deciding to quit. More importantly, we do not need to know who the final winner is. For them, the game transitions from a "bidding" game to something more akin to a "horse race." What we can observe includes the number of participants, the number of actions each participant takes, and the characteristics of the final winner. This brings the modeling approach back to the traditional modeling methods of GR theory.

Our research focuses on the relationships between these actions and characteristics, as well as how the game rules impact these relationships to optimize the game rules or apply them to other tasks. Therefore, we need to review the modeling of auctions:

#### 2.6.2.1 The Psychological and Neurophysiological Foundations of Game Participation and Spectatorship

**Neurophysiological Mechanisms and Psychological Research of Risk-taking**
The basal ganglia (located near the brainstem and primarily responsible for processing activities such as eating, sexual behavior, social behavior, and other rewarding activities), the prefrontal cortex (the control center of the brain), and the limbic system (responsible for emotions and memory) together form the mesolimbic pathway. These systems interact within the mesolimbic pathway to collectively influence how individuals perceive, process, and pursue risks. Each system provides different types of information, helping the brain comprehensively consider decision-making

contexts, thereby making appropriate risk decisions in daily life [64]. This pathway is particularly important in adventurous activities, as it involves assessing uncertainty, potential risks and rewards, and making corresponding behavioral choices.

**Neurophysiological and Psychological Research of Game Spectatorship** During the process of watching sports games, our brain undergoes a series of complex neural mechanisms [65]. First, visual information enters through the eyes and forms images on the retina, which are transmitted to the brain via a three-stage neuron system (including retinal neurons, optic neurons, and lateral geniculate nucleus neurons in the thalamus). This information is then processed in the visual cortex and multiple brain regions such as the occipital, temporal, parietal, and frontal lobes to recognize and analyze game actions and environmental details. In this process, areas containing mirror neurons, such as the temporoparietal junction and the premotor cortex, are activated, as if the brain itself is performing the observed athletes' actions. This neural activity establishes an internal simulation, enabling us to experience these actions at a neural level [66].

Additionally, the brain's emotional processing centers (such as the amygdala and anterior cingulate cortex) are involved in understanding and resonating with the athletes' emotional states, such as excitement or tension [66]. At the same time, cognitive function areas such as the prefrontal cortex are responsible for higher-level cognitive processing of the game, such as strategy understanding and outcome prediction. Spectators may exhibit corresponding physiological responses during watching, such as accelerated heartbeat and muscle micro-movements, reflecting the interaction between the brain and other parts of the body. Finally, the brain's social cognition network is also activated, helping us understand and resonate with the behaviors and emotions of the athletes and other spectators. Through these processes, we can not only watch the game but also "experience" it to a certain extent, including the athletes' actions, emotions, and the game's tense atmosphere, demonstrating the highly developed and complex nature of the human brain in understanding and resonating with others' behaviors [67].

### 2.6.3 Analysis of English Auctions for Observer's Perspective

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. The traditional formulation of information growth (or velocity) in 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 (initial 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 ($S_t$).

$$D = S_t = N_t + 1 + 1 \tag{2.37}$$

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.

$$B = \frac{1}{N_t} \sum_{j=1}^{N_t} |A_h| = \text{Average}(|A_h|) \tag{2.38}$$

Then, the velocity of the auction game can be defined as:

$$v = \frac{1}{2} \frac{\text{Average}(|A_h|)}{S_t} \tag{2.39}$$

Subsequently, the GR and AD of the English auction can be derived:

$$GR = \frac{\sqrt{\text{Average}(|A_h|)}}{S_t} = \frac{\sqrt{B}}{D} \tag{2.40}$$

$$AD = \sqrt[3]{\frac{3 \times \text{Average}(|A_h|)}{S_t^3}} = \frac{\sqrt[3]{3 \times B}}{D^3} \tag{2.41}$$

Table 2.1: Comparison of variable applications between traditional game theory and observer's perspective for English auction analysis

| **Variable** | **Meaning in Traditional Games** | **Meaning in Observer's Perspective** |
|---|---|---|
| $n$ | Number of options or choices available at any point in the game | 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. |
| $S_t$ | Set of all possible game decisions up to time $t$, defining the decision space | Set of all possible auction decisions up to time $t$, defining the decision space. |

In auctions, bidders use their private information to gauge the true value of an item. The final sale price can differ from the estimated value range, known as the price deviation value. Our preliminary study showed higher auction velocities often correlate with larger price deviation values. This indicates that bidders influence the auction's outcome by acting on their private information or emotional investment. The speed of an auction affects the final sale price compared to the estimated price. This is influenced by auctioneer expectations and bidder behavior, resulting in significant price differences. By examining this correlation across price ranges, we gain a deeper understanding of the auction process. It offers valuable insights for auction houses, bidders, and market analysts.

Based on the above theoretical derivations and modeling, this study aims to design and apply AI-driven simulation systems to analyze and predict human decision-making behaviors within auction environments. By integrating Game Refinement Theory and the Motion in Mind framework, this research develops computational models that simulate both rational and irrational behaviors of auction participants under conditions of uncertainty, revealing how participants balance economic utility and non-economic utility. These models provide new insights into group dynamics and individual decision-making patterns within economic contexts. The dual-model system forms a feedback loop, with the internal model examining participants' responses to auction design, while the external model assesses the engagement levels of observers. This approach not only enhances AI's predictive capability in economic scenarios but also benefits virtual markets, recommendation systems, and live-streaming platforms by balancing engagement and strategic insight.

## 2.7 Chapter Summary

In this chapter, we integrate interdisciplinary frameworks into a unified research structure, laying the foundation for theoretical and computational expansions in subsequent chapters. This integration emphasizes how modeling non-economic utility metrics through Game Refinement Theory (GR Theory) and the Motion in Mind framework offers new perspectives on economic decision-making under uncertainty, particularly in auction-based economic transactions where participant behavior, influenced by non-economic utility, deviates significantly from traditional rational behavior models.

Firstly, this chapter combines Game Refinement Theory, the Motion in Mind framework, game theory, utility theory, conspicuous consumption economics, and behavioral economics. Through these frameworks, we analyze not only rational behaviors in economic decision-making but also explore complex human decision-making patterns in auction environments. Our AI-driven system simulates auction participants' behaviors, revealing strategies that balance economic and non-economic utilities under uncertain conditions. These models simulate rational decision-making behavior and capture irrational behaviors, further reflecting psychological and social motivations within real-world economic contexts.

Secondly, the dual-model system based on GR Theory and the Motion in Mind framework evaluates participants' responses to auction designs through an internal model while analyzing observer engagement through an external model. This bidirectional feedback loop enables our research to predict decision-making behavior in economic scenarios and identify methods to balance engagement and strategic insight in applications such as virtual markets, recommendation systems, and live streaming platforms.

This chapter provides the theoretical foundation for further studies in subsequent chapters, especially for the analysis and simulation of economic behaviors under uncertainty and the influence of non-economic utility. This foundation offers new possibilities for understanding and predicting complex market dynamics and group behavior patterns.

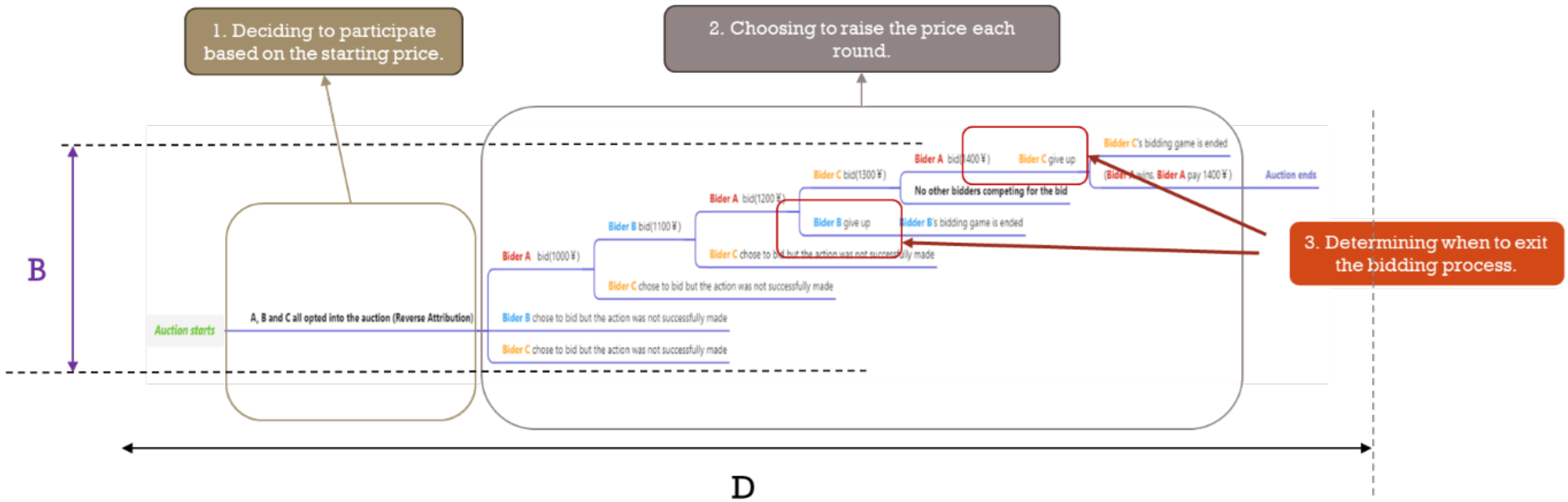



Figure 2-7: Diagram of strategic choices and exit timing in the auction process.[3]

# Chapter 3

# Beyond Economic Incentives: Deconstructing the Multidimensional Motivations in Auction Behavior via Motion in Mind

This chapter explores the appeal of various auction formats through the lens of game refinement theory and Motion in Mind theory, providing a comparative analysis of different auction formats using real auction data from Christie's.

## 3.1 Chapter Introduction

Auctions are a historical economic activity where people propose and accept bids to sell goods or services to the highest bidder or buy from the lowest bidder. The most expensive auction record is for Leonardo da Vinci's "Salvator Mundi," which was sold for $450.3 million in November 2017 [27]. Auctions provide economic benefits and are also a rich application field in game theory and its auction theory subfields [7,10,15]. Thorstein coined the term "conspicuous consumption" for consumers who buy and use expensive goods to show off their wealth [26, 68]. Auctions have non-economic utilities beyond economic benefits for participants, like social value and class identity.

Auctions date back to ancient Babylon and played a significant role in history for over a thousand years [10]. They were popular in ancient Rome [22,29] and also developed in China and India in Buddhist temples [69,70]. Temple auctions were a prominent fundraising practice during the Tang and Song dynasties [23], where deceased monks' personal belongings were sold and proceeds distributed among participating monks after deducting funeral expenses. In 1961, William Vickrey [7] introduced four auction types: Dutch, English, First-Price Sealed Bid, and Second-Price Sealed Bid (Vickrey Auction). Dutch auctions start high and decrease, while English auctions start with a seller-set price and allow for competitive bidding. In the First-Price Sealed Bid Auction, bidders submit one confidential bid, while in the Second-Price Sealed Bid or Vickrey Auction, the highest bidder pays the second-highest bid. This categorization laid the groundwork for understanding auction dynamics [71].

In 1977, the introduction of a new concept that allowed the analysis of auctions without the assumption of independence [24], and classifying any exchange of goods and money as an auction [9], has led to a significant impact on economics, game theory, and auction theory as a whole [30, 72]. Auction design theory was further expanded with innovations like combinatorial and two-sided auctions and blockchain-based mechanisms [73]. Information technology has impacted auction theory, leading to more innovative and complex formats like multi-round decreasing price auctions, popular in the IT industry. They provide an effective commoditized service markets with price-sensitive consumers, such as telecommunications and cloud services, to set prices.

The auction industry has undergone significant innovation with the advent of information technology, making auction activities more convenient and widespread. Auction items range from necessities to luxury goods, representing social status, self-expression, and non-economic value. This study compares English and Dutch Auctions, exploring new ways of measuring market response for unique and scarce items. The study also examines how auctions stimulate participants and enhance the entertainment value of the process. We can better understand their role in modern auction culture by analyzing their socio-economic impact.

The goal of this study involves determining the attractiveness of English auctions, particularly from the game-playing perspective, through the application of game refinement theory and the Motion in Mind concept. The research is divided into four steps: comparative analysis of auction forms, theoretical modeling, accurate data analysis, and conclusion. This study aims to reveal, through theoretical analysis and empirical research, the performance of English auctions as one of the most popular auction forms in terms of game attractiveness, providing new insights into auction theory and practice.

## 3.2 Information, Uncertainty, and Reward

To fully explain game-playing or the act of play as an information artifacts, consider the intertwined nature of information, uncertain, and rewards as a whole system. This involves the revisiting three prominent components: game refinement theory, game progress model, and reinforcement theory.

Game Refinement theory (GR theory) proposes the measure to identify the sophistication and uncertainty of a game's outcome based on the information science perspective, where it provided the utility to increase the game's attractiveness [38,39]. An ideal game has a $GR$ value within the range of $GR \in [0.07, 0.08]$ based on shared patterns of games that were found enjoyable for players of both beginner and advanced skill levels [40]. The formula for measuring $GR$ differs depending on the type of game being analyzed (Equation (3.1)).

$$GR = \frac{\sqrt{B}}{D} = \frac{\sqrt{2G}}{T} = \sqrt{a} \tag{3.1}$$

In this formula, $B$ represents the average branching factor, which is the number of possible options in the game. $D$ stands for game length, or the depth of the entire game tree. $G$ is the average number of successful scores, and $T$ is the average number of attempts per game. Here, $\sqrt{a}$ symbolizes the acceleration of game velocity, reflecting the rate of change in players' information acquisition and decision-making speed throughout the game [41].

By applying the game progress model, we can quantify the decision-making process and perceptual experiences of players within a game. Players learn and perceive through pattern recognition, particularly when faced with unfamiliar abstract concepts, they tend to use analogies for prediction and understanding. In various types of games, players instinctively refer to the laws of physics for cognitive orientation, especially when the game mechanics align with these laws. For example, in chess-like games, players reduce uncertainty as the game progresses, where the amount of information gained at each step is represented by the variable $x(t)$, illustrating the relationship between information and time.

Meanwhile, the game progress model defines velocity ($v$) as the rate at which a player solves uncertainty, while mass ($m$) represents the difficulty of solving uncertainty. Velocity can be expressed as the winning or scoring rate for a game (Equation (3.2)). This model added a temporal development to the original GR theory, which put the concept of 'motion' to represent magnitude and diversity of experience based on the levels of uncertainty [33]. These concepts help to understand how quickly a player can progress and the level of difficulty in the game.

$$v = \frac{B}{2D} = \frac{G}{T} = 1 - m \tag{3.2}$$

The game's third component uses reinforcement theory, which is inspired by the notion of actions (reinforce, punish, and extinct) shaped by their consequences [42] [74]. The variable-ratio reinforcement schedule ($VR(N)$) rewards players regularly after an unpredictable number of responses to maintain their interest [43]. As such, $N$ is associated with the average reward frequency ($1 < N \in \mathbb{R}$) and can be expressed as the inverse of the winning rate $v$ [44].

### 3.2.1 Free Fall Motion in Mind

Solving uncertainty of the outcome of a given thing, like a game, is like a free-fall motion (uniformly accelerated motion) [2]. This implies that the progression is given by (3.3) where $a_0$ stands for the gravity in mind of the observer. On the other hand, a thing is characterized by its velocity as a random reward process. The progression is then given by a linear function (3.4) where $N$ stands for the frequency of variable ratio reinforcement schedule $VR(N)$.

$$y = \frac{1}{2}\, a_0\, t^2 \tag{3.3}$$

$$y = vt \quad \text{where} \quad v = 1/N \tag{3.4}$$

The cross point between the curve (3.3) and the line (3.4), say $(t_{12}, y_{12})$, is determined by (3.5). $T$ is the cross point between the curve (3.3) and $y = t$, which implies $T = 2/{a_0}^2$. Figure 3-1 showed an illustration of the process of solving uncertainty of the outcome of a thing with a focus on the cross point $(t_{12}, y_{12})$ between the straight line (3.4) and gravity-in-mind curve (3.3).

$$y_{12} = y(t_{12}) = y(T/N) = T/N^2 \tag{3.5}$$

The notion of the potential reinforcement energy ($PRE$) is considered as a measurement of objectivity of the outcome of the thing under consideration (see Definition 3) [1]. People would expect to win the reward after $N$ times trials in a random reward event with variable ratio reinforcement schedule $VR(N)$. After multiple trials, it can be conjectured that a stochastic thing is transformed into a deterministic one. It is likely that a random reward event $VR(N)$ (where $N >> 1$) transforms into a deterministic event ($N = 1$) after $N^2$ times trials.

**Definition 3.** *Potential Reinforcement Energy ($PRE$) of a given thing, characterized by its velocity $v$ (hence $N = 1/v$), is defined as a function of the number of trials $\eta$,*

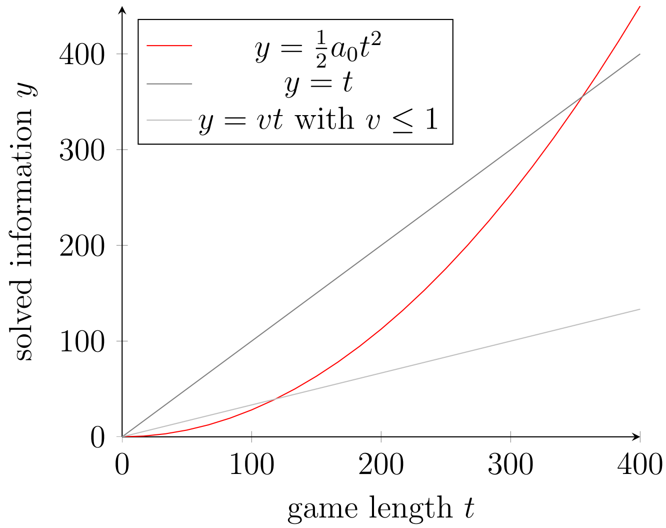



Figure 3-1: An illustration of the process of solving uncertainty of the outcome of a thing: straight line and gravity-in-mind curve.

*which is determined by* (3.6).

$$PRE(\eta) = \eta\ T/N^2 \tag{3.6}$$

Meanwhile, people may experience extraordinary feelings in space due to the different levels of gravity (see Definition 4). This is because we are accustomed (comfort) to the standard gravity on Earth, and any variation can cause discomfort. The standard gravity is represented by $a_0$, whereas any other degree of gravity (e.g., larger), denoted by $a$, may feel uncomfortable or extraordinary.

**Definition 4.** *The magnitude of extraordinary experience $MEE$ is defined as the ratio of extraordinary gravity in mind over the standard one, determined by* (3.7).

$$MEE = \frac{a}{a_0} = \sqrt{N} \tag{3.7}$$

### 3.2.2 Engagement Measure by Balancing Potential Reinforcement Energy ($PRE$) and Magnitude of Extraordinary Experience ($MEE$)

Figure 3-2 illustrates the potential reinforcement energy ($PRE$) and magnitude of extraordinary experience ($MEE$) with a focus on the two cross points [1]. It suggests that people would be highly engaged in a purely random reward event around the cross point between (3.6) with $\eta = N$ and (3.7). On the other hand, people would be highly engaged in a competitive event around the cross point between (3.6) with $\eta = 1$ and (3.7).

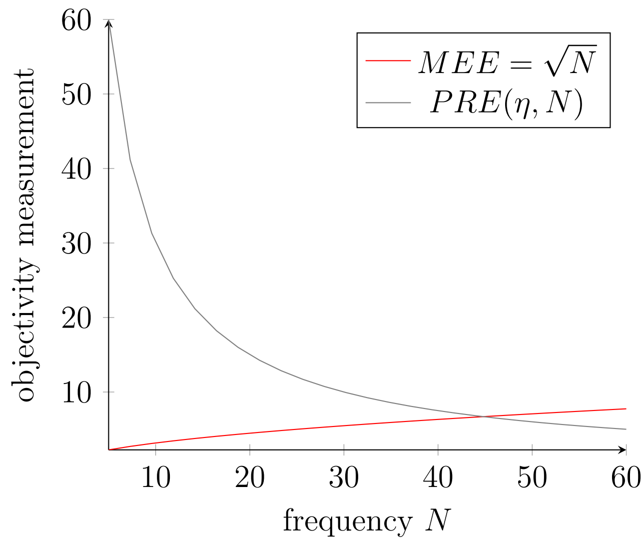



Figure 3-2: An illustration of potential reinforcement energy ($PRE$) and magnitude of extraordinary experience ($MEE$) [1]

Figure 3-2 indicates that an engagement point in the competitive context is around $N = 10$, whereas another engagement point in the purely random context is around $N = 55$. The incomplete information games with some stochastic aspects like card games or Mahjong are so engaged with relatively smaller $N \leq 10$ in the competitive context, rather than skill-based board games like chess with about $N \leq 5$.

## 3.3 Auction System and its Analysis

GR theory and the motion-in-mind framework provided a powerful analytical tool to understand the information dynamics, play experience, and appeal. Based on this consideration, can these tools analyze auctions? The relationship between auctions and games, particularly in the context of leisure games, needs to be established to evaluate this argument. The auction bidding process is fundamentally a strategic game [7]. This leads to the question: Can auctions also be leisure games?

Consumers engaging in conspicuous consumption pay a price exceeding an item's actual value [25]. Auctions can be seen as a leisurely game when participants are less sensitive to final prices [75, 76]. Bidders in some auctions seem less sensitive to the final auction price, indicating that price is not always the primary decision-making factor. This could be due to non-price factors (rarity, emotional value, or strategic purposes) and purchasing power for participating in the auction. For unique items, sentimental or commemorative value may exceed market value. Analyzing decision-making behavior patterns in auction markets should consider non-economic utilities. Real-world auction decisions are complex to measure. In the GR theory and motion-in-mind framework context, players reduce uncertainty as auctions progress. Uncertainty arises from the final sale price or hammer price. Auctions begin with a starting price and end when a winner is declared. The frequency of bids and the success rate of the winner are certain.

In trading, sellers aim for profit, while buyers want low-cost items. Buyers may pay more for prestige. However, auctions are competitive games where buyers set the starting price. As such, the sellers' will is represented in auction rules. In auctions, $I_{before}$ is the information known to the participants before bidding. It can be public or private and influences their decision to bid. The change in bidding price is the most crucial information that impacts their decision to place a bid. The auctions' rules determine the opportunities to make such decisions, as different auctions have varying bid limitations. In auction bidding, participants eliminate uncertainty by moving from an initial price ($I_{price}$) to a final sale price ($F_{price}$). English auctions start from a low initial price ($I_{price}$) and gradually increase through bidding until the final selling price ($F_{price}$) is reached. In contrast, Dutch auctions start from a high initial price ($I_{price}$) and gradually decrease until a participant is willing to bid and make an offer, marking the final selling price ($F_{price}$) and the end of the auction.

In the auction process (regardless of English or Dutch auction), the price changes from the initial price $I_{price}$ to the final selling price $F_{price}$. The relative magnitude of this price change can be measured by comparing the difference between the two. Therefore, based on GR theory and the game progress model, the variable $m$ measures the difficulty of the relative price change process from the initial to the final price (Equation (3.8)). Its value ranges between 0 and 1, where 0 indicates mild competition, and 1 indicates intense competition. This representation works for both English and Dutch auctions and provides a standardized way to assess the magnitude and efficiency of price changes. Note that it would be harder to win the item as the $m$ value becomes larger (difference between $F_{price}$ and $I_{price}$). Since $m + v = 1$, then the velocity of the auction process is then defined by (3.9). Since $N = (v)^{-1}$ by definition, the frequency value of the auction process is then defined by (3.10).

$$m = \frac{|F_{\text{Price}} - I_{\text{Price}}|}{\max(F_{\text{Price}}, I_{\text{Price}})} \quad \text{where} \quad 0 \leq m \leq 1 \tag{3.8}$$

$$v = 1 - m = \frac{\max(F_{\text{Price}}, I_{\text{Price}})}{\min(F_{\text{Price}}, I_{\text{Price}})} \tag{3.9}$$

$$N = \frac{1}{v} = \frac{\min(F_{\text{Price}}, I_{\text{Price}})}{\max(F_{\text{Price}}, I_{\text{Price}})} \tag{3.10}$$

Let $I$ and $F$ be the initial and final prices in an auction, respectively. The win hardness or mass (say $m$) is defined by (3.11). It would be harder to win the target item as the $m$-value (the difference between $F$ and $I$) becomes larger. Since $m+v = 1$ by definition, the velocity of the auction process is then defined by (3.12). Table 3.1 demonstrates the example data of five sessions in an auction system, which is part of an auction with 58 sessions. It is assumed that an auction system, as a competitive event, is characterized by its average velocity of all sessions.

$$m = \frac{F - I}{F} \quad \text{where} \quad 0 \leq m \leq 1 \tag{3.11}$$

$$v = 1 - m = \frac{I}{F} \tag{3.12}$$

Table 3.1: An example data of five sessions in an auction system

| # Session | $I$ | $F$ | $v$ | $N$ |
|---|---|---|---|---|
| 1 | 240,000 | 1,700,000 | 0.14 | 7.14 |
| 2 | 450,000 | 1,000,000 | 0.45 | 2.22 |
| 3 | 14,000,000 | 20,000,000 | 0.70 | 1.43 |
| 4 | 19,000,000 | 42,000,000 | 0.45 | 2.22 |
| 5 | 2,400,000 | 3,000,000 | 0.80 | 1.25 |

In auctions, bidders use their private information to gauge the true value of an item. The final sale price can differ from the estimated value range, known as the price deviation value'. Our preliminary study showed higher auction velocities often correlate with larger price deviation values. This indicates that bidders influence the auction's outcome by acting on their private information or emotional investment. The speed of an auction affects the final sale price compared to the estimated price. This is influenced by auctioneer expectations and bidder behavior, resulting in significant price differences. By examining this correlation across price ranges, we gain a deeper understanding of the auction process. It offers valuable insights for auction houses, bidders, and market analysts.

## 3.4 Result Analysis and Discussions

### 3.4.1 Experimental Design

Our valuation data comes from two reputable auction houses: Christie's (https://www.christies.com) and Sotheby's (https://www.sothebys.com). This public data has been obtained legally and ethically for academic research purposes. We have obtained the initial and final prices of bids, which are essential for our analysis, from the live streams of the auction houses on YouTube (https://www.youtube.com/@christies; and https://www.youtube.com/@sothebys). To ensure the completeness and legality of our data collection process, we have manually recorded and compiled the data. MATLAB R2022b was used to analyze the data for correlation analyses. Table 3.2 and Table 3.3 provide the statistical data of the number of auction sessions based on English auctions.

Table 3.2: Statistical data of several auctions with some number of sessions (English auction system for Christies Hong Kong)

| Auction date | sessions | avg $v$ | avg $N$ |
|---|---|---|---|
| Spring Auction 2021 | 74 | 0.55 | 1.80 |
| Autumn Auction 2021 | 75 | 0.61 | 1.64 |
| Spring Auction 2022 | 58 | 0.67 | 1.48 |
| Autumn Auction 2022 | 53 | 0.68 | 1.47 |
| Spring Auction 2023 | 74 | 0.61 | 1.64 |
| Autumn Auction 2023 | 57 | 0.70 | 1.43 |

Table 3.3: Statistical data of several auctions with number of sessions (English auction system for Christies and Sotheby)

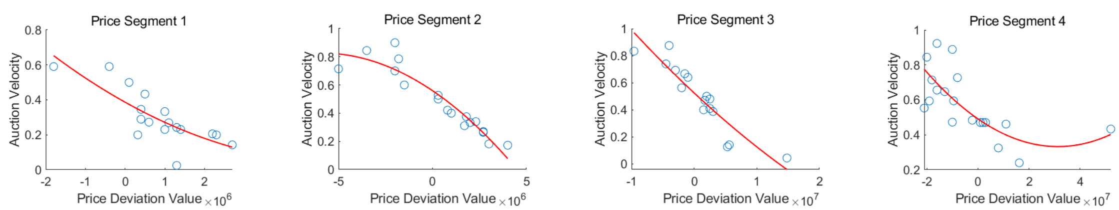
| House | City | Century | Sessions | Avg $v$ | Avg $m$ | Avg $N$ |
|---|---|---|---|---|---|---|
| Christies | London | 20th/21st | 68 | 0.70 | 0.30 | 1.44 |
| Christies | New York | 20th | 65 | 0.63 | 0.37 | 1.59 |
| Christies | Hong Kong | 20th/21st | 57 | 0.70 | 0.30 | 1.43 |
| Sotheby | London | Now | 22 | 0.82 | 0.18 | 1.23 |
| Sotheby | London | Contemporary | 27 | 0.71 | 0.29 | 1.42 |
| Sotheby | New York | Now | 19 | 0.70 | 0.30 | 1.52 |
| Sotheby | New York | Contemporar | 46 | 0.69 | 0.31 | 1.44 |
| Sotheby | Hong Kong | Modern | 39 | 0.71 | 0.29 | 1.42 |
| Sotheby | Hong Kong | Contemporary | 26 | 0.70 | 0.30 | 1.43 |
| Overall | | | 41 | 0.67 | 0.33 | 1.49 |

### 3.4.2 Velocity Analysis of English Auctions

Table 3.4 provide the summary of the 2021 spring and autumn auctions where analysis of the 2021 spring auction has been conducted across four distinct price segments. The auction data analysis indicates a strong negative correlation between price deviation value and auction velocity, meaning that an increase in price deviation value results in a decrease in auction velocity (Figure 3-3). The lowest price segment had a correlation coefficient ($R = -0.7883$), while the second segment (from \$3,650,000 to \$7,050,000) had $R = -0.9251$. In the third price segment (from \$7,050,000 to \$17,000,000), the $R = -0.9187$, and in the highest price segment (from \$17,000,000 to \$202,000,000), $R = -0.6144$. The effect of price deviation value on auction velocity was most pronounced in the second price segment.

Table 3.4: Detailed summary of the 2021 spring and autumn auctions

| **Detail** | **Spring** | **Autumn** |
|---|---|---|
| Total Lots Auctioned | 75 | 77 |
| Lots Withdrawn Before Auction | 1 | 2 |
| Lots Failed to Sell | 2 | 3 |
| Lowest Price | \$500,000 | \$380,000 |
| Maximum Price | \$202,000,000 | \$140,000,000 |

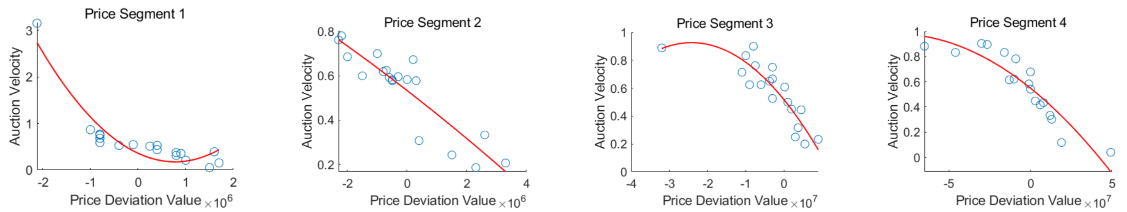



(a) Price segment 1 (b) Price segment 2 (c) Price segment 3 (d) Price segment 4

Figure 3-3: The comparison of (a) segment 1, (b) segment 2, (c) segment 3, and (d) segment 4 in spring auction 2021

For 2021 spring auction, data analysis for different price segments showed that price deviation value negatively correlates with auction velocity, meaning that as price deviation value increases, auction velocity decreases (Figure 3-4). The lowest (\$380,000 to \$3,500,000) and highest price (\$21,750,000 to \$140,000,000) segments had an average auction velocity of 0.62 and 0.57, respectively, with a strong negative correlation ($R = -0.7548$ and $R = -0.8846$, respectively). The second (\$3,500,000 to

$7,400,000) and third price ($7,400,000 to $21,750,000) segments had an average auction velocity of 0.54 and 0.58, respectively, with a very pronounced and consistently strong negative correlation ($R = -0.8992$ and $R = -0.7941$, respectively).



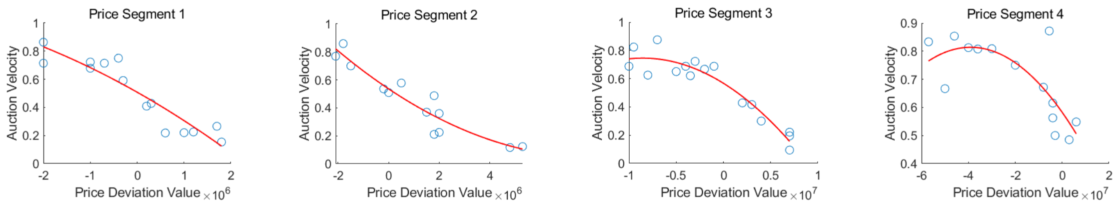

(a) Price segment 1 (b) Price segment 2 (c) Price segment 3 (d) Price segment 4

Figure 3-4: The comparison of (a) segment 1, (b) segment 2, (c) segment 3, and (d) segment 4 in autumn 2021

Table 3.5 provides the summary of the 2022 spring and autumn auctions, where analysis of the 2022 spring auction has been conducted across four distinct price segments, revealing significant insights into the relationship between price deviation value and auction velocity. Higher price deviation values negatively correlate with auction velocity across all price ranges (Figure 3-5). In the range of $800,000 to $3,800,000, a significant increase in price deviation value ($R = -0.9257$) leads to a decrease in auction velocity. In the range of $3,800,000 to $8,000,000, the impact of price deviation value on auction velocity increases as prices rise ($R = -0.9310$). The third price segment of $8,000,000 to $19,500,000 consistently shows a strong negative correlation between price deviation value and auction velocity ($R = -0.9065$). Even in the highest price range of $19,500,000 to $240,000,000, a strong negative correlation between price deviation value and auction velocity remains, although its influence slightly varies ($R = -0.6912$).

Table 3.5: Detailed summary of the 2022 spring and autumn auctions

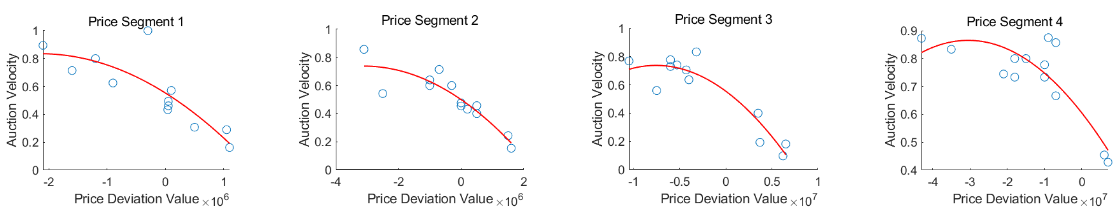
| **Detail** | **Spring** | **Autumn** |
|---|---|---|
| Total Lots Auctioned | 61 | 54 |
| Lots Withdrawn Before Auction | 3 | 3 |
| Lots Failed to Sell | 3 | 8 |
| Lowest Price | $800,000 | $300,000 |
| Maximum Price | $240,000,000 | $70,000,000 |




(a) Price segment 1 (b) Price segment 2 (c) Price segment 3 (d) Price segment 4

Figure 3-5: The comparison of (a) segment 1, (b) segment 2, (c) segment 3, and (d) segment 4 in spring auction 2022

For the analysis, four price segments were considered. The lowest segment, with prices ranging from \$300,000 to \$2,200,000, had an average auction velocity of 0.56 and a strong negative correlation ($R = -0.8106$) between price deviation value and auction velocity (see Figure 3-6(a)). The second segment, costing between \$2,200,000 and \$4,800,000, had an average auction velocity of 0.51 and a pronounced negative correlation ($R = -0.8603$). The third segment, with prices ranging from \$4,800,000 to \$15,000,000, had an average auction velocity of 0.55 and a consistently strong negative correlation ($R = -0.8879$) between price deviation value and auction velocity. In the highest price segment, with prices ranging from \$15,000,000 to \$70,000,000, the average auction velocity was 0.74 with a negative correlation ($R = -0.7093$) between price deviation value and auction velocity that remained strong but slightly varied compared to the other segments.



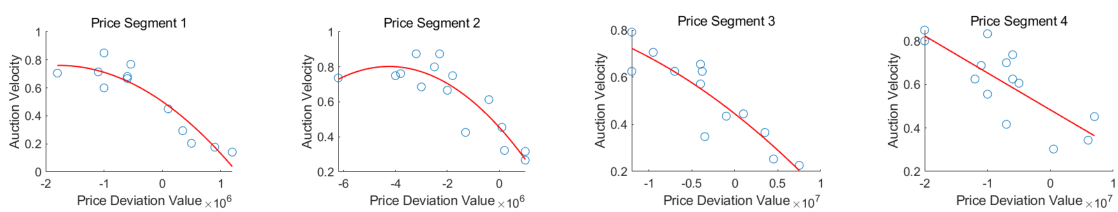

(a) Price segment 1 (b) Price segment 2 (c) Price segment 3 (d) Price segment 4

Figure 3-6: The comparison of (a) segment 1, (b) segment 2, (c) segment 3, and (d) segment 4 in autumn 2021

Table 3.6 provides the summary of the 2023 spring and autumn auctions, where analysis of the 2023 spring auction has been conducted across four distinct price segments, revealing significant insights into the relationship between price deviation value and auction velocity. As the price goes up, the impact of price deviation on auction velocity increases (Figure 3-7). In the lowest price segment ($260,000 to $3,000,000), there was a strong negative correlation ($R = -0.8987$) between price deviation value and auction velocity. In the second segment ($3,000,000 to $8,000,000), there was a very pronounced effect of price deviation value on auction velocity. The third segment ($8,000,000 to $16,000,000) had a consistently strong negative correlation ($R = -0.8921$) between price deviation value and auction velocity. In the highest segment ($16,000,000 to $51,500,000), the negative correlation remained strong but varied slightly.

Table 3.6: Detailed summary of the 2023 spring and autumn auctions

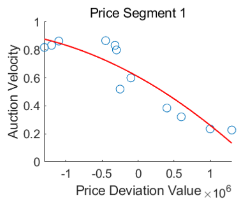
| **Detail** | **Spring** | **Autumn** |
|---|---|---|
| Total Lots Auctioned | 58 | 57 |
| Lots Withdrawn Before Auction | 1 | 4 |
| Lots Failed to Sell | 8 | 7 |
| Didn't pass the auction | 1 | 0 |
| (Not on the sale list at the end) | | |
| Lowest Price | $260,000 | $480,000 |
| Maximum Price | $51,500,000 | $160,000,000 |



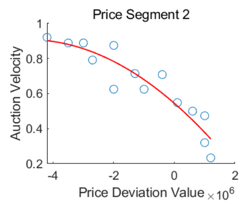

(a) Price segment 1 (b) Price segment 2 (c) Price segment 3 (d) Price segment 4

Figure 3-7: The comparison of (a) segment 1, (b) segment 2, (c) segment 3, and (d) segment 4 in spring auction 2022

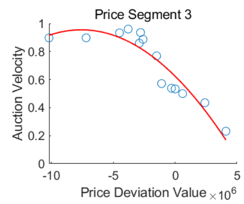
In the lowest price segment ($480,000 to $2,400,000), a higher price deviation value leads to significant reductions in auction velocity, with an average auction velocity of 0.61 and a correlation coefficient ($R = -0.9083$). In the second price segment ($2,400,000 to $4,900,000), the impact of price deviation value on auction velocity becomes more pronounced, with an average auction velocity of 0.65 and a correlation coefficient ($R = -0.9143$). In the third price segment ($4,900,000 to $9,900,000), there is a consistently strong negative correlation ($R = -0.8300$) between price deviation value and auction velocity, with an average auction velocity of 0.71.



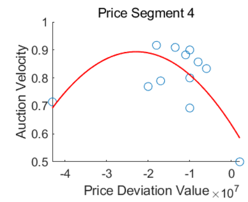

(a) Price segment 1



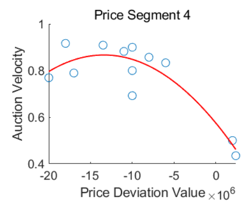

(b) Price segment 2




(c) Price segment 3




(d) Price segment 4(a)




(e) Price segment 4(b)

Figure 3-8: The comparison of (a) segment 1, (b) segment 2, (c) segment 3, (d) segment 4(a), and (e) segment 4(b) in autumn 2021

In the highest price segment (\$9,900,000 to \$160,000,000), a weak negative correlation was observed ($R = -0.1167$) between price deviation value and auction velocity (see Figure 3-8). Lot 33, as illustrated in Figure 3-8(d), was an outlier that significantly influenced the overall correlation analysis. Notably, Lot 33 was estimated to range from \$55,000,000 to \$85,000,000 but reached a final sale price of \$42,000,000. After excluding Lot 33, the adjusted price range for this segment reflected a strong negative correlation ($R = -0.7263$) between price deviation value and auction velocity, as shown in Figure 3-8(e), highlighting the importance of outlier analysis in understanding auction dynamics.

#### 3.4.2.1 Interpretation of Observed Correlations

These results indicate that the correlation analysis and curve shapes provide insights into the underlying mechanisms. Specifically, the negative correlation between price deviation and auction velocity seems to be driven by a balance between rational and irrational decision-making processes among participants.

**Mechanisms Behind the Observed Correlation:**

- **Economic Rationality in the Low-Price Segment:** In the low-price segment, participants' decisions are influenced not only by rational considerations but also by private values such as emotional attachment. These private values effectively impact participants' behavior, causing deviations from strictly rational economic utility. This is reflected in the concave curve, where larger price deviations are closely associated with lower auction velocity. Greater price deviation often indicates the introduction of new information that influences participants' decisions. At this stage, participants tend to act quickly, as their perceived cost of making incorrect decisions is relatively low. Instead, their motivation to use the auction as a platform to express personal values or signals to the external world becomes stronger. These signals could include demonstrating financial capability, supporting a favored artist, or promoting a particular artistic style.

- **Shift to Partial Rationality in the Mid-to-High Price Segments:** As prices increase, participants exhibit a return to rationality, with their decision-making becoming more aligned with economic considerations. Consequently, the influence of "price deviation," as an external information variable, diminishes. This shift results in the curve transitioning from concave to convex. During this phase, the cost of signaling through auction behaviors rises, leading participants to place greater weight on economic returns in their decision-making.

This transformation illustrates how participants balance economic and non-economic factors when making bidding decisions. The dynamic interplay between rationality and irrationality explains the changes in curve shapes across different price segments. These behavioral shifts reflect the complex motivations of auction participants and underscore the importance of integrating both economic and behavioral frameworks into auction studies.

**Future Work:** The current correlation analysis serves as a preliminary exploration. In future research, I plan to conduct an in-depth investigation into the roles of psychological expectations, costs, and social status signals. This will provide a more comprehensive understanding of the factors shaping participants' behavior in auction settings.

New analysis of English auction data has shown that auction velocity and price deviation exhibit a clear negative correlation (Figure 3-9 and Figure 3-10). This relationship is further broken down into four price segments, highlighting distinct behaviors within each segment. As the final price increases, the auction velocity decreases due to the market's increasing caution. This phenomenon reflects the bidders' hesitation in high-value auctions, where they take more time to strategize and bid carefully.

**Figure 3-9: Cumulative Price Deviation versus Auction Velocity.** This figure visualizes the negative correlation between price deviation ($\Delta$) and auction velocity ($v$) across four distinct price segments:

- **Segment 1 (Blue):** Represents low-price auctions. The steep curve suggests high sensitivity of auction velocity to price deviation, as bidders react quickly to slight deviations.

- **Segment 2 (Red):** Corresponds to mid-price auctions, where velocity decreases less steeply as deviation increases.

- **Segment 3 (Green):** Displays a more gradual change, indicating that for high-price auctions, velocity remains relatively stable despite price deviation. This behavior suggests bidder caution.

- **Segment 4 (Black):** Represents very high-price auctions with a flatter curve, showing minimal velocity changes as price deviation increases. This reflects a cautious and stable bidding environment.

Interestingly, when the final sale price matches the auction house's upper limit estimate ($F_p \approx E_u$), the auction velocity stabilizes at approximately $v \approx 0.54$. This

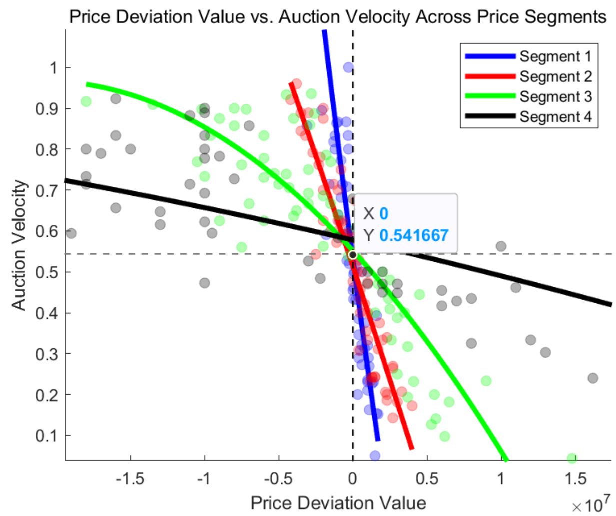
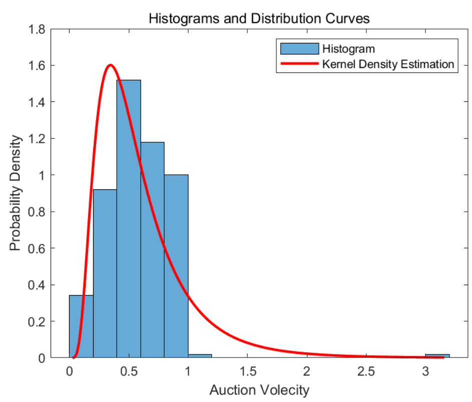
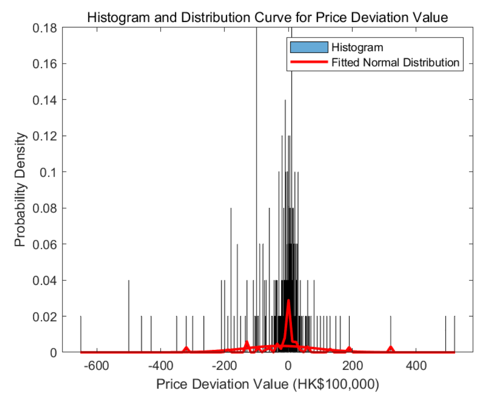


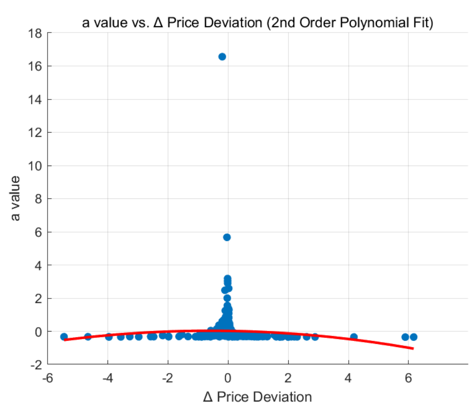

Figure 3-9: Cumulative price deviation ($\Delta$) versus auction velocity ($v$)across segments of 2023 auction



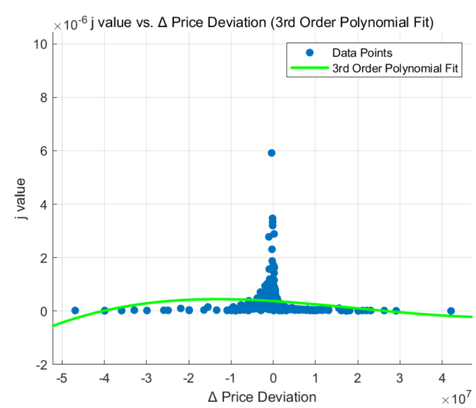

(a) Auction velocity histograms and distribution curves




(b) Price deviation value histograms and distribution curves




(c) $a$ value versus $\Delta$ price deviation




(d) $j$ value versus $\Delta$ price deviation

Figure 3-10: The comparison of (a) auction velocity and (b) price deviation against distribution curves. Meanwhile, (c) $a$ value and (d) $j$ value versus price deviation state, which we term *information alignment*, indicates a balance between bidders' private valuations and the common value of the auction item. It resembles a complete information game, where the transparency of information reduces strategic uncertainty. At this point, price deviation($\Delta$) $\approx 0$, and both acceleration ($a$) and jerk ($j$) values reach their peaks (Figure 3-10c and Figure 3-10d). These peaks reflect heightened market activity and rapid dynamic adjustments by bidders as they align their strategies in response to the reduced uncertainty.

**Figure 3-10: Analysis of Auction Dynamics.**

- **(a) Auction velocity histograms and distribution curves:** This subfigure shows the distribution of auction velocities across all price segments. The peak at $v \approx 0.5$ highlights the most frequent auction velocity, where auctions reach a balance between rapid bidding and cautious decision-making. The kernel density estimation (red curve) reveals a positively skewed distribution, indicating that most auction velocities are concentrated around the peak, with fewer instances of extremely high velocities. The long tail extending up to $v \approx 3$ reflects the occasional occurrence of high auction velocities, likely due to outlier events or specific auction strategies.

- **(b) Price deviation value histograms and distribution curves:** This subfigure illustrates the distribution of price deviations across auctions. To ensure comparability, all auction prices were converted into Hong Kong dollars (HKD) using real-time exchange rates at the time of transaction. Most deviation values are concentrated near $\Delta \approx 0$, with the majority of data points falling within a range of $|\Delta| < 50$. This indicates that the majority of auction outcomes closely align with the estimated upper limit price, reflecting a state of information alignment in the market. In this state, bidders' private and common values converge, resulting in more predictable and consistent market behavior. Conversely, higher absolute deviation values ($|\Delta| > 100$) are significantly less frequent, as reflected in the long tails of the distribution. These tails exhibit a degree of asymmetry and discreteness, suggesting potential outlier events or exceptional auction dynamics. While the fitted normal distribution curve (red line) approximates the data well near the peak, it deviates in the tails, indicating that extreme deviations may not follow a perfect normal distribution. This deviation arises because excessively large price deviations are often influenced by external factors—such as unique auction items, rare market conditions, or strategic bidding behaviors—which affect the decision-making of certain participants. Such events, however, are low-probability occurrences and are unlikely to significantly affect the overall market behavior or the majority of participants.

- **(c) Acceleration ($a$) versus price deviation ($\Delta$):** The second-order polynomial fit shows that acceleration ($a$) peaks when price deviation($\Delta$) $\approx 0$, indicating rapid changes in auction velocity. This reflects bidders' active response to aligning their strategies during information alignment.

- **(d) Jerk ($j$) versus price deviation ($\Delta$):** Similarly, the third-order polynomial fit shows that jerk ($j$) reaches its highest value near price deviation($\Delta$) $\approx 0$, indicating intense adjustments in acceleration. This suggests a dynamic bidding process at the information alignment point.

These figures demonstrate that auction dynamics are highly dependent on price deviation. When $\Delta \to 0$, the auction velocity across all price segments converges to $v \approx 0.54$. This indicates a consistent pattern where the influence of price deviation diminishes, and the bidding dynamics align regardless of the price segment. However, acceleration ($a$) and jerk ($j$) peak at this point, reflecting intense market activity. These rapid adjustments by bidders are closely tied to the degree of information alignment.

### 3.4.3 In-depth Analysis of Initial and Final Auction Estimates

A preliminary analysis of the positions of $I$, $F$, $E_L$, and $E_U$ values can offer insights into the auction dynamics, as illustrated in Figure 3-11. Four cases can be outlined based on the different interplay of auction estimates (see Table 3.7).

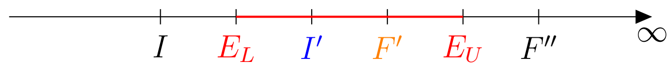



Figure 3-11: Auction dynamics based on the positioning of $I$, $F$, $E_L$, and $E_U$ values

In Cases 1 and 3, if $F = F'$, the auction game is restricted, and $N$ is typically between 2 and 3, requiring high skillfulness. In Cases 2 and 4, where $F = F'$ regardless of the initial price, the restriction on the auction game length is removed. In such cases, the final auction price is limited only by the funds of the second-highest bidder, leading to an increase in $N$ and decrease in the required skill level. However, incorrect information or misjudgments may still result in financial losses. After analyzing these different cases, we can infer that if an auction house wants to set a smaller $v$ value for an auction, there are two main strategies:

1. The first approach is to select an item with a significantly higher $F$ and set the initial bid ($I$) conspicuously below public expectations. This means that by keeping $F$ relatively large or fixed, the $I$ value is set smaller. While this method is straightforward, it may be too obvious for auction participants.

2. To increase the Price Deviation Value, announce an estimate range significantly below the public's psychological expectations before the auction. This is a classic financial strategy called "Money on the table." It makes the participants perceive that the asset is undervalued and encourages them to bid on the item. However, this approach could lead to an unintended scenario where information about the item's value is widely disseminated before the auction. The auction house might have to start bidding at a price equal to or higher than the lower estimate limit to ensure fairness.

Assuming the auction house adopts the first strategy, which involves not manipulating the published estimate but selecting an item with a significantly higher Final Price to set its starting auction bid. An examination of real initial price data from auction houses, as illustrated in Figure 3-12, reveals that the distribution of initial

Table 3.7: Auction estimate cases

| **Case** | **Notation** | **Descriptions** |
|---|---|---|
| 1. Typical estimate | $I < E_{\mathrm{L}}$ & $F \in [E_{\mathrm{L}}, E_{\mathrm{U}}]$ | If the auction house's published estimates are accurate, meaning the estimate range meets the public expectations, i.e., Common Values $\in [E_{\mathrm{L}}, E_{\mathrm{U}}]$, and the initial price is below the lower limit of the estimate, $I < E_{\mathrm{L}}$. Then, the Final Price depends on the second highest bidder's Private Values, i.e., the minimum between the bidder's Maximum Willingness to Pay (MWP) and the Purchasing Power Limitation (PPL), $\min(\mathrm{MWP}, \mathrm{PPL})$. When the accurate estimate predicts the actual transaction price, i.e., $F$ exactly falls within the estimate range, $F = F'$ and $F \in [E_{\mathrm{L}}, E_{\mathrm{U}}]$. It follows that $v_1 = \frac{I}{F'}$ with $\frac{I}{E_{\mathrm{L}}} \leq v_1 \leq \frac{I}{E_{\mathrm{U}}}$. |
| 2. High Bidder's Private Value | $I < E_{\mathrm{L}}$ & $F > E_{\mathrm{U}}$ | In the second case, while the auction house's estimate range is accurate with$I$ value suggesting $I < E_{\mathrm{L}}$, the bidder's private value, influenced by additional information, is higher. When the second highest bid exceeds$E_{\mathrm{U}}$, resulting in $F > E_{\mathrm{U}}$ as illustrated in Figure 3-11 as $F''$, where $F = F''$. This leads to $v_2 = \frac{I}{F''}$ and $v_2 \geq \frac{I}{E_{\mathrm{U}}}$, clearly indicating $v_2 > v_1$. |
| 3. Influence of New Information Prior to Auction | $I > E_{\mathrm{L}}$ & $F \in [E_{\mathrm{L}}, E_{\mathrm{U}}]$ | In the third scenario, influenced by new information received before the auction bidding or by intentional design by the auction house, $I > E_{\mathrm{L}}$ (denoted as $I = I'$), and if the estimate range is accurate, i.e., the market's common values fall within $[E_{\mathrm{L}}, E_{\mathrm{U}}]$ as shown in Figure 3-11 as $F'$, where $F = F'$. Consequently, $v_3 = \frac{I'}{F'}$. If $I' = E_{\mathrm{L}}$, then $v_3 = \frac{I'}{F'} \leq \frac{E_{\mathrm{L}}}{E_{\mathrm{U}}}$. If $I' > E_{\mathrm{L}}$, then $v_3 = \frac{I'}{F'} \geq \frac{E_{\mathrm{L}}}{E_{\mathrm{U}}}$, and $v_3 > v_2$. |
| 4. Changes in Common Values or Underestimated Auction House Estimates | $I > E_{\mathrm{L}}$ & $F > E_{\mathrm{U}}$ | In the fourth case, common values change due to new information in the market, or the auction house's estimate range is significantly below market expectations, leading to $I = I'$ and $F = F''$. In this scenario, $v_4$ can vary, but it is certain that $v_4 < v_3$. |

price predominantly concentrates between 60% to 90% of the lower estimate limit, accounting for 81.15% of the total data. In contrast, initial prices significantly below the lower estimate limit, such as starting bids lower than 50% of the lower estimate limit or auctions without a reserve price/estimate, only constitute 7.24%. This indicates that using the first strategy is not common among auction houses.

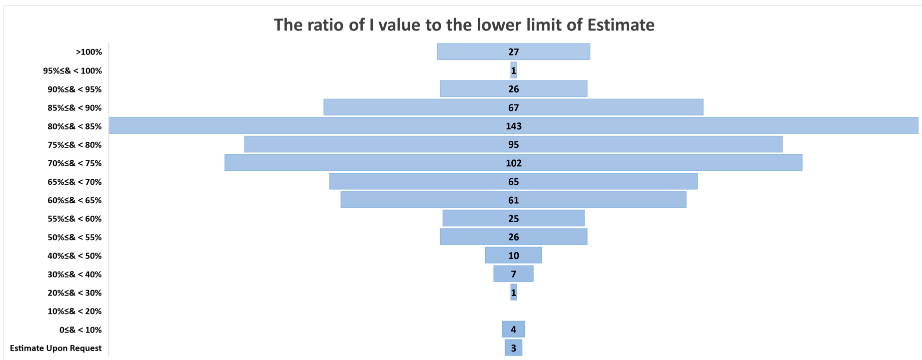



Figure 3-12: The ratio of initial price ($I$) to the lower limit of estimates ($E_L$)

The first strategy for auction houses involves selecting an item with a significantly higher $F'$ to set its starting auction bid without manipulating the published estimate. Most initial prices fall between 60% and 90% of the $E_L$ limit, making up about 81.15% of the total data. Only 7.24% of prices fall below the $E_L$ limit. Although auction houses do not commonly use the first strategy, the second strategy may be difficult to observe in data. However, extreme cases where $v$ is small and $N$ is large suggest its potential occurrence. The first strategy directly impacts the initial price but is rare in auction data. The second strategy subtly influences auction outcomes by setting the stage for higher engagement and values, leveraging the psychological aspect of bidding behavior without lowering the initial price.

### 3.4.4 Potential Extraordinary Engagement $PEE$ – Balance between $PRE$ and $MEE$

Accurate market valuation and consideration of market expectations while setting starting prices are crucial for effective auction strategies. The correlation between price deviation and auction velocity highlights the importance of precise valuation and strategic planning for auction houses and sellers. This information provides valuable insights for understanding and succeeding in auctions, emphasizing the need for detailed market analysis.

The results obtained from the English auction indicate that the auction can be viewed as a competitive skill-based game for $N \leq 3$. Three years of English auction data analysis shows larger differences between the actual transaction prices and the estimates, leading to a decrease in auction velocity (see Figure 3-9). When the final sale prices align with the auction house estimates, the market operates at peak efficiency ($v \approx 0.54$). This state can be compared to the interplay between bidders and auction houses, where there is a balance between inertial and external forces.

In the context of auctions, inertia refers to the tendency of bidders to stick to the auction house's estimated valuation range [77]. This range is determined based on public information and historical data and acts as a baseline expectation for the bidders. It creates a form of cognitive inertia, where initial valuations of bidders gravitate towards these figures, which is influenced by loss aversion, causing bidders to pay a premium to win sooner [77, 78]. However, just like physical objects that maintain their motion unless acted upon by an external force, the final bid prices in an auction are also subject to change when new information or bidder sentiments come into play (such as consumer preferences [79]).

External forces, such as bidders' private information, personal valuation, and emotional attachment, can influence auctions. For instance, certainty and anchoring bias could lead to distorted bidding [80] and justified envy [81], while bidders with external incentives tend to overbid due to the influence of disclosure rule [82]. This can significantly deviate from the initial estimates provided by the auction house. The price deviation value metric highlights the difference between the estimated and actual selling prices, indicating whether the item was undervalued or had unique appeal to certain bidders.

A complex interplay of inertia and external forces influences the potential extraordinary engagement ($PEE$) between underlying factors and auction players. This interplay is further shaped by initial, final, and estimated pricing dynamics, which impact price deviation and the progression of price velocity [83]. As seen in a human competitor's presence, the social-competitive aspect of auction tasks also modulates bid outcome processing [84]. Interestingly, the discussion of these different dynamics, described by the progression of the price velocity, is left for future study.

## 3.5 Chapter Conclusion

This study examines English auctions through game refinement theory. It reveals that winning in an auction is not just about acquiring high-value items at minimal costs. Bidders are motivated by financial strength, personal or artistic expression, industry recognition, and pleasure from the auction process. These motivations highlight the psychological and social aspects of auction participation.

Auctions need to cater to bidder preferences to succeed. Designing an experience that satisfies diverse motivations and draws potential bidders is key. Economic, psychological, and social dimensions should be considered, especially for new or economically diverse participants. Observing, learning, and assessing item value and auction feasibility are crucial for potential bidders.

Our study highlights the importance of strategic pricing and market analysis in auctions. Our research reveals the factors that influence bidder behavior and auction outcomes. We offer practical recommendations for auctioneers to design successful auction strategies. Our study comprehensively views auctions as a complex strategy, expression, and engagement game.

One interesting point is the importance of attention in auctions, which goes beyond being a resource used by bidders to ensure that they get the best possible outcome. It is also a strategic asset that can enhance one's social status through conspicuous consumption. Being able to capture and hold the attention of peers not only affects the immediate outcome of the auction but also serves as a means of social signaling, indicating success and prestige. As a result, the auction environment becomes a complex interplay of economic strategy, cognitive limitations, and social dynamics, where the allocation of attention plays a central role. As such, attention is vital for future research.

# Chapter 4

# Strategic Selection and Design of the First Auction Item: Analyzing Auction Dynamics through "Motion in Mind" and "Potential Reinforcement Energy"

This chapter is an updated and abridged version of the following publication:

- Li, S., Khalid, M.N.A., Iida, H. (2024). Strategic Selection and Design of the First Auction Item: Analyzing Auction Dynamics through "Motion in Mind" and "Potential Reinforcement Energy". Asia-Pacific Journal of Information Technology and Multimedia, Vol.13 (2), 298–312

## 4.1 Chapter Introduction

The auction market is a significant component of the economic market. Unlike negotiated markets, auctions follow specific transaction rules, making them a vital area for studying resource allocation and price formation [7]. Auctions adhere to rules set and announced by the organizers, with bidders placing bids within a specified timeframe according to these established rules, and completing the payment transaction as per the rules once bidding concludes. The clear transaction rules and defined transaction timeframe have attracted numerous economists and game theory researchers, including many Nobel laureates in economics, to focus on auctions as a research field [14].

The complexity and competitiveness of the auction process create a classic game structure where participants' dynamic decisions and actions during auctions can be modeled, enriching the theories and applications in game theory and its subfield, auction theory [15]. Auction dynamics have been extensively studied to understand how various factors influence bidder behavior and auction outcomes. Traditional methods typically focus on economic and strategic factors, such as bidder rationality, auction formats, and price determination mechanisms. These studies have laid a solid foundation for understanding the fundamental economic interactions that occur during auctions.

Professor Iida and his colleagues have long been dedicated to research based on game and game behavior, proposing the Game Refinement Theory. Recent theoretical developments have introduced new dimensions to auction dynamics analysis, such as the "Motion in Mind" framework, which offers a new perspective on the field [33]. In our previous research, we found that auctions exhibit significant "non-economic utilities" based on the concept of "conspicuous consumption" [68], where participants display their wealth and social status by owning and using these items [26]. This behavior aligns with the efforts of game participants to "win." When participants are not particularly sensitive to the auction's final price, auctions can be viewed as a form of entertainment [85]. The game psychology and the duration of the game in auctions can significantly impact bidders' participation and decision-making processes. We analyze auctions using the "Motion in Mind" framework, which emphasizes the psychological dynamics bidders experience during auctions, influencing their perception of value and willingness to continue participating.

Similarly, the "Potential Reinforcement Energy" framework introduces a new method for understanding auctions by focusing on the reinforcement and motivational aspects of bidding [1]. This theory suggests that auctions are not just economic transactions but involve complex psychological engagement that can profoundly affect bidder behavior. By examining the potential energy bidders accumulate through the anticipation and fulfillment of winning bids, this framework provides insights into the emotional and psychological rewards of participation.

This paper focuses on the analysis of the first auction item in each English auction. English auctions have a long history, dating back approximately 2,500 years to ancient Babylon as recorded by Herodotus in the 5th century BC [10]. Auction houses, such as the renowned Christie's and Sotheby's, established in 1744 and 1766 respectively, also have a long history. The design of the auction order for each auction item by auction houses has been proven effective through historical examination. The first auction item plays multiple roles, setting the tone for the auction, establishing the bidding pace, and attracting potential bidders. The design of the first auction item by auction houses can significantly influence the overall rhythm and competitive environment. By carefully selecting and designing the first item (considering factors like price range, starting price, expected price, and auction game speed), auction houses can manipulate the dynamics of the auction to enhance bidder participation and maximize final outcomes.

## 4.2 Information, Uncertainty, and Reward

Our analysis employs three pivotal theories to dissect the essence of game playing and its manifestation in auctions: the Game Refinement Theory, the Game Progress Model, and Reinforcement Theory.

Game Refinement ($GR$) theory assesses a game's allure and the predictability of its outcomes through an information science lens, suggesting that a $GR$ value between 0.07 and 0.08 denotes optimal player engagement [38–40]. The computation of $GR$ is tailored to the game type and involves metrics such as average branching factor ($B$), game length ($D$), successful scores ($G$), and attempts per game ($T$):

$$GR = \frac{\sqrt{B}}{D} = \frac{\sqrt{2G}}{T} = \sqrt{a} \tag{4.1}$$

The Game Progress Model quantifies how players' perceptions evolve during gameplay, particularly as they draw analogies to decipher new patterns and abstract concepts. This model mathematically expresses the resolution of uncertainty as velocity ($v$) and the complexity of decisions as mass ($m$), enhancing our understanding of strategic thinking in games that reflect real-world physics:

$$v = \frac{B}{2D} = \frac{G}{T} = 1 - m \tag{4.2}$$

Reinforcement theory complements this by considering how game outcomes (rewards, punishments) shape player behavior through variable-ratio reinforcement schedules ($VR(N)$), which sustain engagement by delivering rewards at unpredictable intervals [42, 43, 74].

### 4.2.1 Cognitive Dynamics in Games

The analogy of free-fall motion describes players' experience of resolving uncertainties in games, akin to uniformly accelerated motion influenced by mental gravity, depicted in the following equations:

$$y = \frac{1}{2}\, a_0\, t^2 \tag{4.3}$$

$$y = vt \quad \text{where} \quad v = 1/N \tag{4.4}$$

The intersection of these dynamics at specific points (Equation (4.5)) illustrates the peak of uncertainty resolution during gameplay, providing a visual representation in Figure 4-1.

$$y_{12} = y(t_{12}) = y(T/N) = T/N^2 \tag{4.5}$$

Figure 4-2 illustrates the potential reinforcement energy ($PRE$) and magnitude of extraordinary experience ($MEE$) with a focus on the two cross points [1]. It suggests that people would be highly engaged in a purely random reward event around the

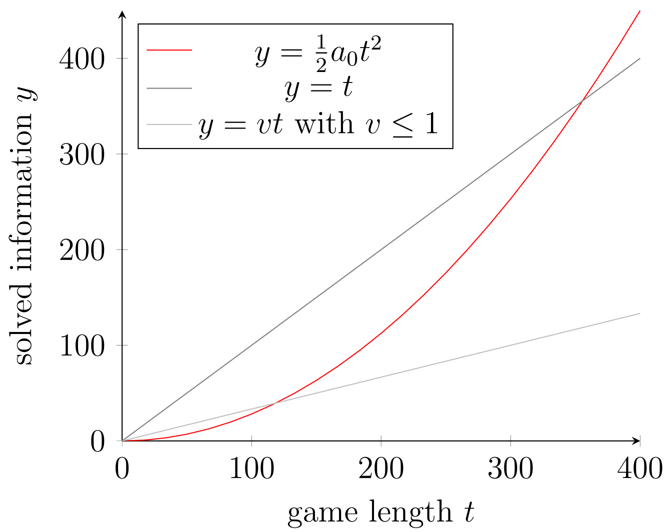



Figure 4-1: An illustration of the process of solving uncertainty of the outcome of a thing: straight line and gravity-in-mind curve.

cross point between (4.6) with $\eta = N$ and (4.7). On the other hand, people would be highly engaged in a competitive event around the cross point between (4.6) with $\eta = 1$ and (4.7).

**Definition 5.** *Potential Reinforcement Energy (PRE) quantifies the energy exerted by players in navigating challenges, expressed as:*

$$PRE(\eta) = \eta\, T/N^2 \tag{4.6}$$

**Definition 6.** *Magnitude of Extraordinary Experience (MEE) gauges the intensity of mental exertion relative to a normative baseline, calculated as follows:*

$$MEE = \frac{a}{a_0} = \sqrt{N} \tag{4.7}$$

Figure 4-2 indicates that an engagement point in the competitive context is around $N = 10$, whereas another engagement point in the purely random context is around $N = 55$. The incomplete information games with some stochastic aspects like card games or Mahjong are so engaged with relatively smaller $N \leq 10$ in the competitive context, rather than skill-based board games like chess with about $N \leq 5$.

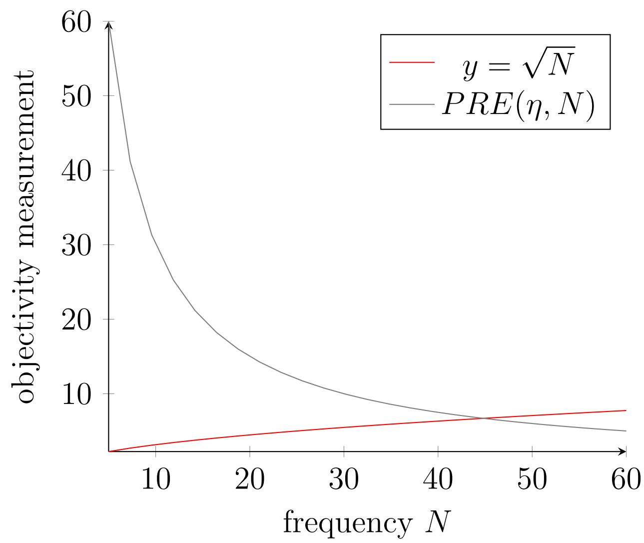



Figure 4-2: An illustration of potential reinforcement energy ($PRE$) and magnitude of extraordinary experience ($MEE$)

### 4.2.2 Applying Game Dynamics to Auction Analysis

Integrating GR theory and cognitive dynamics into auction analysis offers novel insights into bidder strategies and behaviors, reflecting how deeply game theory concepts are interwoven with the mechanics of auctions. This section delves into the application of these theoretical frameworks to various auction formats, highlighting their utility in unraveling the complex interactions and strategic decisions of auction participants.

### 4.2.3 Analytical Framework for Auction Dynamics

This section provides an analysis of the auction system through the combined perspectives of GR theory and the Motion-in-Mind framework. It emphasizes the parallels between auction dynamics and game mechanics, particularly within the realm of leisure games, where the act of bidding itself is inherently a strategic game. In these settings, auction participants often exhibit reduced sensitivity to the final price outcomes, influenced by factors such as the item's rarity, emotional significance, or strategic use, along with their financial capacity.

Whether in English or Dutch auction formats, the transformation from an initial asking price, $I_{\text{price}}$, to the final selling price, $F_{\text{price}}$, serves as a key metric. The extent of this price transformation is assessed by the relative change between the initial and final prices. Drawing on GR theory and the game progress model, we define the metric $m$ to quantify the challenge presented by the price change throughout the auction (Equation 4.8), where $m$ ranges from 0 (indicative of mild competition) to 1 (indicative of intense competition). The concepts of velocity and frequency of the auction are quantified next (Equations 4.9 and 4.10).

$$m = \frac{|F_{\text{Price}} - I_{\text{Price}}|}{\max(F_{\text{Price}}, I_{\text{Price}})} \quad \text{where} \quad 0 \leq m \leq 1 \tag{4.8}$$

$$v = 1 - m = \frac{\max(F_{\text{Price}}, I_{\text{Price}})}{\min(F_{\text{Price}}, I_{\text{Price}})} \tag{4.9}$$

$$N = \frac{1}{v} = \frac{\min(F_{\text{Price}}, I_{\text{Price}})}{\max(F_{\text{Price}}, I_{\text{Price}})} \tag{4.10}$$

These equations standardize our approach to analyzing the dynamics of auction pricing, allowing for a deeper understanding of the strategic decision-making processes in auction markets, beyond just economic factors.

Two points warrant further clarification. Firstly, despite the variance in currency across different auction markets, this study focuses exclusively on the relative numerical differences in prices, avoiding currency conversion to ensure a more focused analysis of the psychological and strategic impacts of these price variations. Secondly, given the high stakes typically involved in art auctions, where bid increments are substantial, we adjust our analysis to align with cognitive processing patterns commonly observed in humans; both the initial and final prices are normalized by the smallest bid increment. This normalization not only aids in simulating a sense of acceleration in the bidding process but also mirrors the psychological state and strategic decisions of the bidders during the auction.

## 4.3 Methodology

In our study, data were sourced from the world's leading auction houses, Christie's and Sotheby's. We accessed public auction data through their official websites and YouTube channels. To ensure the legality of our data collection process, we refrained from using web scraping techniques and instead opted for manual data collection. After acquiring the data, we utilized MATLAB R2022b for conducting correlation analysis and multivariate regression modeling, which facilitated the modeling of participant perspectives.

Moreover, our analysis was bifurcated into two distinct viewpoints: the observer and the participant. Using game trees and game refinement theory, we analyzed the behaviors and motivations of viewers during the auction process and their impact on auction dynamics. This analysis helps us understand how observers perceive various dynamics of the game by witnessing the actions of the participants, potentially motivating them to transition from mere viewers to active participants.

From the participant's perspective, i.e., the bidders, we focused on analyzing the influence of starting bids, final prices, and the pace of the auction on their decision-making processes. Additionally, a comparative analysis was conducted, comparing the starting and final prices and the pace of the first auctioned item against the averages for other items in the auction.

These comprehensive analyses not only enhance our understanding of auction dynamics but also provide strategic insights for auction houses on designing auction processes and items to attract more participants. Our findings illustrate that auctions are not merely economic transactions but involve complex psychological and social dynamics, characterizing them as strategic games.

## 4.4 Results

In this study, we compared the first lots of Christie's and Sotheby's auctions in different regions (Hong Kong, London, New York) with the average data of the entire

Table 4.1: Comparison of the First Lot of the Auction vs. Average Data

| **Auction** | **The First Lot of the Auction** | | | | **Avg. data for One Auction** | | | |
|---|---|---|---|---|---|---|---|---|
| | BID | M | V | N | BID | M | V | N |
| C HK '23 | 34 | 0.768 | 0.232 | 4.313 | 8 | 0.302 | 0.698 | 1.433 |
| C LD '23 | 14 | 0.733 | 0.267 | 3.750 | 9 | 0.305 | 0.695 | 1.438 |
| C NY '23 | 18 | 0.652 | 0.348 | 2.875 | 11 | 0.371 | 0.629 | 1.590 |
| S HK '23 Mod | 25 | 0.833 | 0.167 | 6.000 | 7 | 0.295 | 0.705 | 1.418 |
| S HK '23 Cont | 17 | 0.688 | 0.313 | 3.200 | 8 | 0.303 | 0.697 | 1.435 |
| S LD '23 Now | 23 | 0.771 | 0.229 | 4.375 | 12 | 0.460 | 0.540 | 1.852 |
| S LD '23 Cont | 8 | 0.438 | 0.563 | 1.778 | 8 | 0.294 | 0.706 | 1.417 |
| S NY '23 Now | 20 | 0.814 | 0.186 | 5.385 | 13 | 0.340 | 0.660 | 1.516 |
| S NY '23 Cont | 15 | 0.742 | 0.258 | 3.875 | 12 | 0.306 | 0.694 | 1.442 |
| Overall | 19 | 0.716 | 0.284 | 3.950 | 10 | 0.331 | 0.669 | 1.504 |

Note 1: C: Christie's; S: Sotheby's  Note 2: HK: Hong Kong; LD: London; NY: New York
Note 3: Mod: Modern; Cont: Contemporary

auction. We found that the first lots exhibited significant attractiveness and artistic value in multiple dimensions. Specifically, the average number of bids (BID) for the first lots was 19, compared to the average of 10 for the entire auction, indicating higher market attention from participants. Additionally, the average game mass ($m$ value) for the first lots was 0.716, much higher than the overall auction average of 0.331, suggesting that the first lots typically had higher game quality. In terms of game velocity ($v$ value), the first lots had an average value of 0.284, lower than the overall average of 0.669, reflecting more intense competition among participants. Finally, the average game frequency ($N$ value) for the first lots was 3.950, significantly higher than the overall average of 1.504, indicating that the first lots triggered more frequent bidding activities.

### 4.4.1 Game Analysis

From the perspective of early GR theory, as shown in the table below, the overall auction's game nature resembles a score game. However, the data of the first lots resemble more of board game data, and even reach the level of major public gambling data.

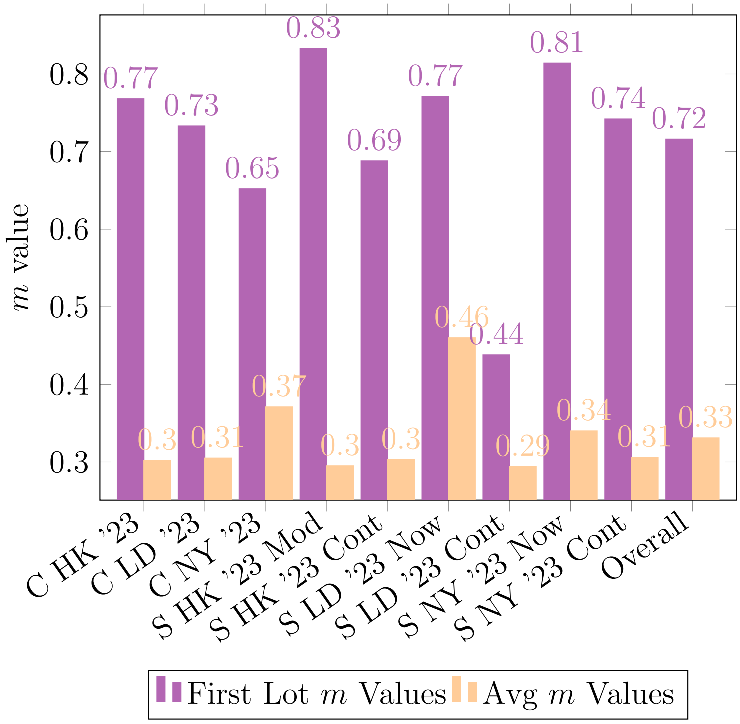



Figure 4-3: Comparison of $m$ value: First Lot vs Average for One Auction

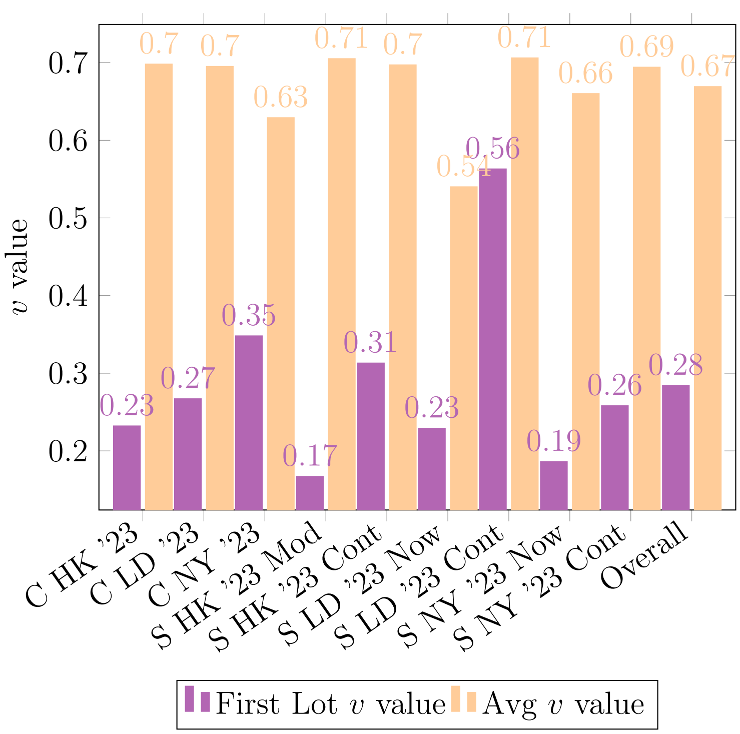



Figure 4-4: Comparison of $v$ value: Average vs First Lot for One Auction

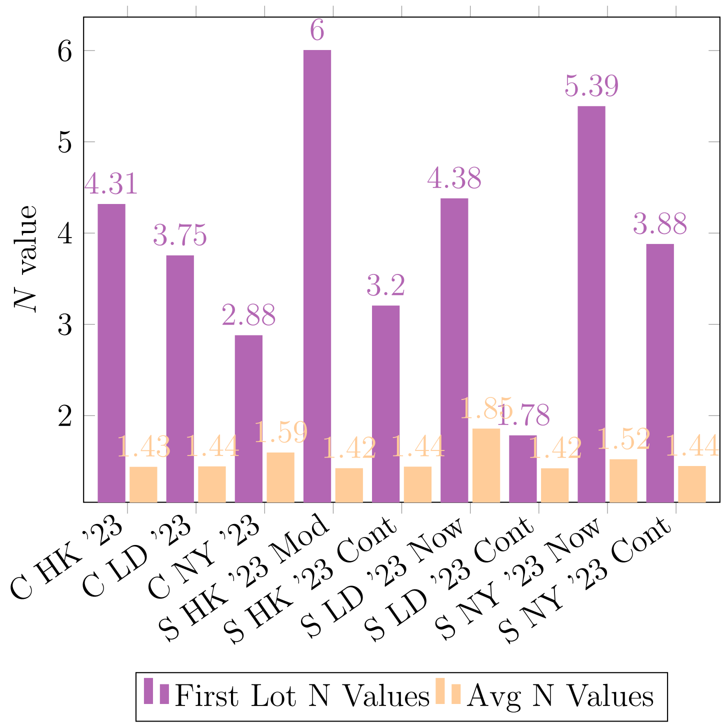



Figure 4-5: Comparison of N Values: First Lot vs Average for One Auction

### 4.4.2 Understanding the Motivations and Addiction Mechanisms Behind the $m$ value in Auctions

In an auction environment, the $m$ value of a lot reflects its level of uncertainty and challenge, significantly impacting participants' behavior and psychological responses. According to the research "Objectivity and Subjectivity in Games: Understanding Engagement and Addiction Mechanism [33]," in high-risk and uncertain decision-making environments, people tend to overestimate the psychological impact of potential losses compared to gains of the same value.

The average $m$ value of the first lots is 0.716, significantly higher than the average $m$ value of all lots in the entire auction, which is 0.331. This significant difference reveals the uniqueness of the initial lots in attracting participants: a higher $m$ value indicates these lots have greater uncertainty and challenge, making them more attractive. The higher $m$ value of the first lots (average 0.716 as shown in Table 4.2) indicates that these initial lots are not only more challenging but also likely to evoke a stronger sense of potential victory, thus stimulating more active participation. This

Table 4.2: Game Analysis

| Category | Game | v | m |
|---|---|---|---|
| **Board Games** | Chess | 0.22 | 0.78 |
| | Shogi | 0.35 | 0.65 |
| | Go | 0.60 | 0.40 |
| **Sports** | Soccer | 0.11 | 0.89 |
| | Badminton | 0.58 | 0.42 |
| | Basketball | 0.27 | 0.73 |
| | Table tennis | 0.50 | 0.50 |
| **Major Public Gambling** | Online casino | 0.96 | 0.04 |
| | Pachinko/Pachislot | 0.85 | 0.15 |
| | Horse race | 0.80 | 0.20 |
| | Speedboat race | 0.75 | 0.25 |
| | Bicycle race | 0.75 | 0.25 |
| | Auto race | 0.70 | 0.30 |
| | Lottery | 0.46 | 0.54 |
| **English Auction** | Average Data | 0.67 | 0.33 |
| | The First Lot | 0.28 | 0.72 |

psychological state can lead to higher engagement and addictive behavior, as participants, especially those who did not win the lot, become more actively involved in subsequent bids to win.

For auction organizers, understanding the differences in $m$ value between the first lots and overall lots is crucial for designing auction strategies. By placing more challenging lots at the beginning of the auction, organizers can effectively increase initial interest and overall auction activity. Meanwhile, organizers should adjust strategies for subsequent lots to maintain participants' interest and engagement.

### 4.4.3 Impact of Auction Pricing Strategies

How do auction houses achieve this design? In our analysis of auction pricing dynamics, we observed significant differences between the initial prices and final prices of the first lots and the entire auction. We converted all prices to a common currency, USD, for consistency in analysis.

Table 4.3: Auction Data

| Auction | Currency | The First Lot of the Auction | | | Average Data | | |
|---|---|---|---|---|---|---|---|
| | | $I_P$ | $F_P$ | $H_{PP}$ | $I_P$ | $F_P$ | $H_{PP}$ |
| C HK '23 | HKD | 1,600,000 | 6,900,000 | 5,300,000 | 8,185,283.019 | 11,731,698.11 | 3,546,415 |
| C LD '23 | GBP | 24,000 | 90,000 | 66,000 | 593,893.9394 | 854,015.1515 | 260,121 |
| C NY '23 | USD | 800,000 | 2,300,000 | 1,500,000 | 5,537,619.048 | 8,802,777.778 | 3,265,159 |
| S HK '23 Mod | HKD | 200,000 | 1,200,000 | 1,000,000 | 3,821,081.081 | 5,418,918.919 | 1,597,838 |
| S HK '23 Cont | HKD | 500,000 | 1,600,000 | 1,100,000 | 10,286,086.96 | 14,758,695.65 | 4,472,609 |
| S LD '23 Now | GBP | 48,000 | 210,000 | 162,000 | 328,285.7143 | 607,857.1429 | 279,571 |
| S LD '23 Cont | GBP | 450,000 | 800,000 | 350,000 | 1,327,142.857 | 1,880,000 | 552,857 |
| S NY '23 Now | HKD | 65,000 | 350,000 | 285,000 | 1,711,667 | 2,595,278 | 883,611 |
| S NY '23 Cont | HKD | 200,000 | 775,000 | 575,000 | 3,297,717.391 | 4,753,695.652 | 1,455,978 |

Note 1: C: Christie's; S: Sotheby's Note 2: HK: Hong Kong; LD: London; NY: New York
Note 3: Mod: Modern; Cont: Contemporary
Note 4: $I_P : InitialPrice; F_P : FinalPrice; H_{PP} : HammerPricePremium$

Specifically, the average starting price of the first lots was approximately \$1,098,229, while the average final price was approximately \$4,588,888, with an average price increase of \$3,490,659. In contrast, the average starting price for the entire auction was approximately \$4,289,171, with an average final price of \$6,445,888, resulting in an average price increase of \$2,156,717.

These findings indicate that there is usually a significant escalation in bidding activity during the auction, with initial prices and final prices generally being much higher compared to the first lots. This difference in pricing and price increase suggests that while the first lots attract great interest, they typically start at lower prices and achieve substantial gains, whereas the overall auction starts at higher initial prices and achieves larger absolute price increases.

This provides auction organizers with important insights into how to optimize auction processes and strategies to maximize engagement and ensure the health and sustainability of auction activities. By precisely setting the starting prices of lots, organizers can regulate market expectations and participants' psychology, thereby influencing the activity level and final success rate of the entire auction.

### 4.4.4 Lure Bidding Model: Strategic Insights for Auction Design

In traditional games, higher game velocity or lower game mass makes the game feel more skill-based, while lower game velocity makes the game more challenging, requiring more skill. However, in auctions, participants experience a unique combination of "game stimulation" (non-economic utility) and "economic stimulation."

Based on this observation, auction houses adopt a specialized design strategy akin to using lures in fishing: instead of bait, lures mimic small fish to trigger larger fish's hunting instinct. Similarly, the first auction item serves as a low-cost entry, offering bidders confidence in their financial capability and returns—referred to as economic utility. The higher $m$ value of this item leads bidders to overestimate their skills, functioning as a psychological 'lure' that boosts engagement.

Additionally, the "Serial Position Effect" ensures the first auction item remains memorable, influencing participants' bidding behavior throughout the event. By leveraging this effect, auction houses can strategically place highly engaging lots early in the auction to maximize overall engagement and ensure a dynamic auction atmosphere.

To explore this further, we designed a *Lure Bidding Model* for AI participants in subsequent simulations (Algorithm 1). This model adjusts participants' self-assessment based on their initial experiences, reflecting both confidence-building and psychological engagement mechanisms. The conceptual basis of the Lure Bidding Model can also inspire applications in computer game design, where balancing skill and challenge plays a critical role in maintaining player engagement.

**Algorithm 1** Lure Bidding Model

[1]Initialize parameters $\alpha$, $\beta$, $\gamma$

Set personal valuation $PV$ and social status value $SV$

Calculate initial maximum willingness to pay: $MWP \leftarrow \alpha \times PV + \beta \times SV$

Set purchasing power limit $PPL$ Determine the final price: $Final\_Price \leftarrow \min(MWP, PPL)$

**if** new information is received **then** Adjust $MWP$ based on new information: $MWP\_new \leftarrow MWP + \gamma \times New\_information\_impact$

Update auction velocity: $v \leftarrow I_P/F_P$ *$I_P$: initial price, $F_P$: final price

**return** $Final\_Price$, $MWP\_new$, $v$

The Lure Bidding Model provides auction organizers with actionable insights into designing the auction flow, particularly the strategic placement of the first item to maximize engagement. The dual influence of economic utility and game utility further reinforces the importance of psychological factors in auction dynamics, making the design of the first lot a pivotal aspect of successful auctions.

## 4.5 Discussion

The first auction item not only sets the pace of the auction but also establishes an important psychological benchmark for the participants. This benchmark profoundly influences the subsequent behavior of all bidders, whether they actively participate in the first bid or merely observe. The auctioning process of the first item is not just about the highest bidder winning; it broadly showcases the complex interplay of strategy, psychology, and social status. According to neurological research, particularly the principles of mirror neurons, spectators experience a sense of enjoyment as if they are personally competing. This phenomenon is discussed in our other paper, "Rational Bidding Meets Emotional Viewing: The Landscape of English Auction Livestreams in the Age of Algorithms [86]." Moreover, if a qualified participant hesitates before the first auction item is auctioned, the observed intense competition may stimulate their interest and ultimately lead them to decide to participate.

As a psychological anchor, the first auction item sets expectations for the value and engagement of the auction for both active bidders and spectators. This plays a crucial role in maintaining the consistency of the auction design, thereby enhancing competitiveness. Bidders' behavior is not only driven by potential economic gains but also by the opportunity to express personal taste, seek social recognition, and satisfy emotional needs.

Furthermore, the role of social dynamics in auctions cannot be overlooked. Auctions are often public performances where bidders display their economic and cultural capital [68]. Understanding these psychological and social motivations is essential for comprehensively grasping bidder behavior, which transcends mere economic transactions.

## 4.6 Implications for Auction Design

The findings of this study provide several practical recommendations for auction houses regarding the strategic placement and pricing of items. By deeply understanding the diverse motivations of bidders, auction houses can design their auctions to maximize financial returns and enhance bidder engagement and satisfaction.

Firstly, strategically placing auction items with high game mass at the beginning of the auction can stimulate higher engagement and sustained competitive bidding. This method leverages the initial excitement and sets a high standard for value growth, potentially increasing the overall yield of the auction. The effectiveness of this strategy can be quantified by the price change game mass and game velocity($m = \frac{F-I}{F}$ and $v = 1 - m = \frac{I}{F}$, where $I$ is the initial price, and $F$ is the final price). This ratio reveals the price changes from the beginning to the end of the auction and is a key indicator of auction vitality.

Secondly, understanding the various motivations of bidders—from investment and collection to social signaling and personal satisfaction—enables auction houses to tailor their marketing and cataloging strategies to attract a broader audience. This can include detailed provenance, artist background, and the significance of the items to enhance emotional and social appeal.

Assuming the bidder's maximum willingness to pay (MWP) is related to the purchasing power limit (PPL), the final bid can be expressed as:

$$F = \min(\mathrm{MWP}, \mathrm{PPL})$$

When bidders select an auction item within a suitable price range as the first item, we can further analyze this dynamic mathematically. Assuming the bidders' motivation is determined by their psychological expectations of the item's value and the need for social expression, we can quantitatively describe their bidding decision process with the following formula:

$$\mathrm{MWP} = \alpha \times PV + \beta \times SV$$

where $PV$ represents the personal valuation of the item, and $SV$ represents the potential social status enhancement from acquiring the item. $\alpha$ and $\beta$ are parameters that adjust the influence of these two factors.

In the context of market information updates or changes in bidder preferences, MWP may be adjusted based on new information, affecting the final $F$. This dynamic can be modeled by introducing an adjustment factor $\gamma$ to simulate the impact of new information:

$$\text{MWP}_{\text{new}} = \text{MWP} + \gamma \times \text{new information impact}$$

where $\gamma$ indicates the sensitivity of bidders' willingness to pay to new information.

Since bidders continuously observe the entire auction, we can consider the auction of the first item as an "advertising event." This "advertising event" serves as a comprehensive "new information impact" that ultimately influences the participation willingness of all auction participants.

Finally, potential changes and innovations in auction design could include the integration of technology to provide more immersive and interactive bidding experiences. For instance, virtual reality technology could allow bidders to visualize items in their own space before purchasing, enhancing emotional connection and perceived value. Additionally, leveraging data analytics to better predict bidding patterns and preferences can lead to more personalized and engaging auctions.

## 4.7 Chapter Conclusion

This study illuminates the significant impact that strategic selection and design of the first auction item have on auction dynamics. By employing the "Motion in Mind" and "Potential Reinforcement Energy" frameworks, we have demonstrated how the initial item sets the tone for the entire auction, influencing bidder engagement, competition intensity, and final auction outcomes.

Key findings reveal that the first auction item not only establishes a psychological benchmark for participants but also significantly drives the auction's pace and bidder motivation. The higher game mass (m value) and lower game velocity (v value) of the first items compared to overall auction averages underscore their role in creating a more competitive and engaging environment. These metrics provide auction houses with critical insights into optimizing auction design to maximize participant engagement and final sale prices.

Additionally, our analysis of auction data from Christie's and Sotheby's showcases how the initial item's starting price and final bid price can significantly deviate from the overall auction trends, emphasizing the unique role of the first lot in driving bidder behavior. This insight highlights the necessity for auction houses to carefully curate the initial item, balancing between attractive starting prices and the potential for significant price increases.

Future research directions include exploring the long-term effects of initial item design on auction house reputation and bidder loyalty, as well as integrating advanced technologies like virtual reality to enhance bidder experience. Moreover, further studies could delve into the psychological aspects of auction participation, particularly the emotional and social incentives that drive bidding behavior.

In conclusion, the strategic design and placement of the first auction item are pivotal in shaping auction dynamics. By understanding and leveraging the psychological and motivational factors at play, auction houses can enhance bidder engagement, drive higher competition, and ultimately achieve more successful auction outcomes. This research not only contributes to auction theory but also offers practical implications for optimizing auction practices in the competitive market landscape.

# Chapter 5

# Enhancing Auction Experiences: Game Dynamics and Customer Experience Design

## 5.1 Chapter Introduction

The auction market, a vital component of the broader economic landscape, operates under specific, predefined rules, differentiating it from negotiated markets. These rules, crucial for studying resource allocation and price formation, attract significant interest from economists and game theorists, including Nobel laureates [7, 14]. Auctions create a structured competitive environment where bidders' decisions can be systematically analyzed, contributing to both game theory and auction theory [15]. The history of auction houses is profoundly ancient. The two most renowned English auction houses are Sotheby's and Christie's, with Sotheby's established in 1744 and Christie's in 1766 [11].

Meanwhile, Dutch auction activities can be traced back to 1887, initially for selling fruits and vegetables [87]. As the status of the Dutch maritime coachmen was established and the Dutch financial industry developed alongside the tulip economy, the Dutch auction system gradually matured. Over the years, auction houses have developed a deep understanding of auction rules, including the assessment, authentication, and pricing of auction items, how many items to set up for auction simultaneously, and the order in which items appear. This condition has turned each auction into a well-designed game with its set dynamics.

In the realm of customer experience (CX) design, understanding psychological principles such as the Serial Position Effect and the Peak-End Rule can significantly enhance the way auctions are structured and perceived by participants [88]. The Serial Position Effect suggests that participants are more likely to remember the first and last items in a sequence more vividly than those in the middle [89]. This effect highlights the importance of strategically designing an auction's initial and concluding moments to create memorable and impactful experiences. Auction houses can optimize participants' engagement and satisfaction by ensuring that key auction items are placed at the beginning and end of the event.

Similarly, the Peak-End Rule, proposed by psychologist Daniel Kahneman, posits that people's overall assessments of an experience are heavily influenced by the most intense (peak) moments and the final part of the experience [90]. In the context of auctions, designing high points of excitement and ensuring a positive conclusion can lead to a more favorable overall evaluation of the auction experience. Even if some parts of the auction are less engaging, an intense peak moment and a satisfying ending can significantly enhance participants' recollection and enjoyment of the event.

The research conducted by Iida et al. has long focused on game theory and human behavior, culminating in the development of the Game Refinement Theory. Recent theoretical developments have introduced new dimensions to auction dynamics analysis, such as the "Motion in Mind" framework, which offers a new perspective on the field [33]. In our previous research, we found that auctions exhibit significant "non-economic utilities" based on the concept of "conspicuous consumption" [25], where participants display their wealth and social status by owning and using these items [26]. This behavior aligns with the efforts of game participants to "win." When participants are not particularly sensitive to the auction's final price, auctions can be viewed as a form of entertainment [85]. The game psychology and the duration of the game in auctions can significantly impact bidders' participation and decision-making processes. We analyze auctions using the "Motion in Mind" framework, emphasizing the psychological dynamics bidders experience during auctions, influencing their perception of value and willingness to continue participating.

This article delves into the intricate relationship between game dynamics—precisely game velocity and game mass—and customer experience (CX) design within competitive environments like auctions. With their inherent game-like qualities, auctions are a prime example of how these dynamics can be leveraged to craft engaging and satisfying participant experiences. By examining the design strategies employed by auction houses, we aim to illustrate how manipulating game velocity and mass can significantly improve CX in similar competitive scenarios. Game velocity refers to the pace at which uncertainty unfolds, affecting participants' perception of game progress and urgency. Conversely, game mass pertains to the game's density and degree of difficulty, influencing the depth and challenge of participant engagement. The interplay between game velocity and game mass determines the overall rhythm and richness of the experience, directly influencing participants' emotional and cognitive involvement.

In scenarios where participants are not obligated to act in every round, their attention may naturally gravitate towards the aspects of the game that are rich in game mass. This observation underlines the importance of thoughtful game design in enhancing participant engagement and satisfaction. Through the lens of game theory and CX principles, our analysis provides insights into optimizing these game dynamics to maximize participant satisfaction and engagement in auctions. By doing so, we aim to enhance the auction experience and offer a broader framework for improving CX in competitive and strategic environments.

Traditional economic models often assume that participants make rational decisions based solely on economic utility. However, in practice, people frequently make choices driven by factors such as identity, class, honor, or sheer enjoyment—what we might call "game utility." Though seemingly irrational from an economic perspective, these decisions adhere to their logical framework, prioritizing hedonic over economic utility. Understanding these "game incentives" is crucial, as they represent a significant reason people engage in competitive environments like auctions. This perspective broadens our understanding of human decision-making, revealing the limitations of conventional economic models and underscoring the importance of considering "game dimensions" in studying competitive economic environments.

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The research presented here bridges existing gaps in traditional auction studies, which have primarily focused on rational decision-making and static market mechanisms. By addressing overlooked dimensions—such as non-economic motivations, dynamic decision processes, and social factors like audience effects—this study makes three pivotal contributions. First, it introduces a systematic behavior modeling framework, providing a robust foundation for analyzing complex bidder interactions. Second, it pioneers a methodology for quantifying non-economic utilities, shedding light on the often-misunderstood drivers of auction behavior. Finally, it delves into audience effects as a critical yet underexplored factor in auction dynamics.

This innovative approach, integrating advanced frameworks like Game Refinement Theory and Motion in Mind Framework, contrasts sharply with conventional methods that rely on isolated problem-solving or qualitative descriptions. By offering robust, quantitative tools, the study not only enhances theoretical understanding but also opens avenues for practical applications, such as designing engaging economic systems. This study leverages advanced computational techniques to simulate auction scenarios, integrating AI-driven decision models to enhance the predictive accuracy of bidder behavior. These contributions not only bridge economic and computational fields but also demonstrate the potential of algorithmic solutions in optimizing real-world auction designs. By utilizing computational models and AI-driven simulations, this research provides a novel approach to analyzing and optimizing auction dynamics. This interdisciplinary perspective highlights the transformative role of computer science in enhancing the understanding and application of economic systems.

## 5.2 Theories of Customer Experience in Commercial Behavior

Auctions, inherently competitive economic transaction events, exhibit characteristics of both economic and gamified nature. Considering their economic attributes alongside their commercial properties, one might ponder the existence of customer experience within auctions. Furthermore, considering the gamified nature of auctions compels us to consider the game experience aspect. Discussing customer experience inevitably leads us to the design of customer journey paths and touchpoints. The auction environment, fraught with innumerable interactions and decisions, is shaped by its participants' perceptions, behaviors, and cognitive biases. Understanding these underlying psychological dynamics is essential for designing auction mechanisms that are both effective and user-friendly. Classical cognitive theories such as the serial position effect and the peak-end rule provide profound insights for optimizing auction design and strategy by analyzing the trajectory through which participants engage in the bidding process.

### 5.2.1 Serial Position Effect

The serial position effect is a cognitive phenomenon emphasizing a unique pattern of recall accuracy for a series of items, where individuals tend to remember the first (primacy effect) and last (recency effect) items more vividly than those in the middle. This effect highlights the importance of strategically designing the initial and concluding moments of customer interaction to create memorable experiences [89]. Leveraging this cognitive bias ensures that key contact points at the beginning and end of a service or product interaction are optimized for active participation, thereby significantly impacting the overall perception and satisfaction of customers [91]. Thus, the serial position effect provides a valuable framework for businesses to enhance customer retention and loyalty by focusing on the psychological foundations of memory and satisfaction.

### 5.2.2 Peak-End Rule

The peak-end rule proposed by psychologist Daniel Kahneman [90] suggests that people's memories and overall assessments of an experience (such as an event or period) are not based on the average level of happiness throughout the experience. Instead, evaluations are primarily influenced by the most intense (peak) emotions experienced, and the emotions felt at the conclusion (end) of the experience. Essentially, people's evaluations of an experience are determined by the most intense positive or negative emotions during the process and the final emotional state.

This principle has numerous practical applications, including customer experience, healthcare services, and holiday planning. It indicates that to enhance people's evaluations of an experience, the focus should be on amplifying the climax or peak moments of the experience and ensuring a positive conclusion. Even if there are less pleasant parts during the experience, a strong peak moment and a positive ending can lead to a positive recollection of the experience.

This study focuses on analyzing the first and core auction items. The rationale behind this selection is their significant impact on the overall auction dynamics and customer experience. Due to the constraints of the journal's length requirements and the nature of auctions where participants can leave at any time, this paper does not include the analysis of the last auction item, as it is challenging to define which item is the last for most participants. However, future research can extend the current study to include a comprehensive analysis of the previous auction item to provide a more holistic view of auction dynamics.

## 5.3 Motion in Mind Model

### 5.3.1 Principle Review

Building upon the game refinement theory (GR theory), the motion in mind framework explores gaming dynamics from the perspective of a bidder's cognitive process in an auction [92]. For instance, just as a player in a board game needs to balance speed and strategy to progress, an auction participant must balance their bidding speed with strategic decisions based on perceived value and competition intensity [93]. This concept revolves around the idea that the rate of successful information acquisition fundamentally influences a game's progression. Here, the speed or velocity of the game, denoted by $v$, signifies the player's success rate in overcoming uncertainties or challenges.

Interestingly, the perceived quality of the game inversely correlates with its velocity, based on a zero-sum game payoff function. This is expressed as $m = 1 - v$, where a velocity of $v = \frac{1}{2}$ indicates equal probabilities of winning and losing. This concept underscores the intricate balance between the rate of success and the game's inherent challenges, impacting player engagement and perception of the game. This formulation, previously applied in the study of fairness in games such as Scrabble, is expressed as Eq. (5.1). It also highlights the intricate balance between the rate of success and the game's inherent challenges, impacting player engagement and perception of the game [94].

$$\vec{p} = m \cdot v = (1 - v) \cdot v \tag{5.1}$$

Moreover, the framework introduces the concept of game momentum ($\vec{p}$), which measures the likelihood that players will continue to engage and focus on the game. This momentum is influenced by the players' tendency to persist in playing, even as the difficulty level fluctuates. Essentially, $\vec{p}$ represents the momentary trend based on the current game speed, akin to the momentum of a moving object in physics. It reflects the effort required to change the game state and the players' propensity to maintain engagement and focus, especially when their success rate remains constant. Thus, a high value of $\vec{p}$ suggests a player's optimal effort in balancing challenges and abilities, maximizing engagement with the game. Meanwhile, the concept of potential energy in this framework, denoted as $E_p$, relates to the energy stored in the game system at its initial state. This energy is analogous to the players' expectations of achieving a particular game state and is quantified in the following equation:

$$E_p = 2mv^2 \tag{5.2}$$

The $E_p$ value depends on winning rates and the player's energy and expectations. It signifies the amount of game information necessary for players to progress and is associated with their desire to complete the game and the level of comfort experienced in winning. This concept of potential energy provides game designers with a tool to assess the stability and complexity of a game, enhancing the player's experience and engagement. In short, the motion in Mind framework complements the Game Refinement Theory by offering a deeper understanding of the psychological and cognitive elements at play, highlighting how players interact with and perceive the game dynamics.

### 5.3.2 Modeling in Auction

The auction system is analyzed using GR theory and the motion-in-mind framework to understand information dynamics and play experience. The relationship between auctions and leisure games is explored, where the bidding process is a strategic game influenced by non-price factors (like rarity, emotional value, or strategic purposes) and purchasing power. In the auction process, be it English or Dutch auctions, the price transitions from an initial price ($I_{\text{price}}$) to a final selling price ($F_{\text{price}}$). The relative magnitude of this price change is evaluated by comparing the difference between these prices. Consequently, based on GR theory and the game progress model, the variable $m$ measures the difficulty of the relative price change process from the initial to the final price (Eq. (5.3)), where its value ranges from 0 to 1, indicating mild to intense competition. The auction's velocity and frequency are then defined by Eq. (5.4) and Eq. (5.5), respectively. Through these formulas, we standardize the assessment of the magnitude and efficiency of price changes, further analyzing decision-making behavior patterns in auction markets and considering non-economic utilities [85].

$$m = \frac{|F_{\text{Price}} - I_{\text{Price}}|}{\max(F_{\text{Price}}, I_{\text{Price}})} \quad \text{where} \quad 0 \leq m \leq 1 \tag{5.3}$$

$$v = 1 - m = \frac{\max(F_{\text{Price}}, I_{\text{Price}})}{\min(F_{\text{Price}}, I_{\text{Price}})} \tag{5.4}$$

$$N = \frac{1}{v} = \frac{\min(F_{\text{Price}}, I_{\text{Price}})}{\max(F_{\text{Price}}, I_{\text{Price}})} \tag{5.5}$$

Two essential clarifications are necessary. First, although different auction markets use other currencies, this study focuses on the impact of the numerical differences represented by prices on auction participants. Thus, auction amounts are not converted to uniform currency values. This approach allows for a purer analysis of price changes' psychological and strategic impacts. Second, considering that the bidding prices in the art auction market are typically high for each bid increment, we adopt a method that conforms to the human brain's habitual information processing by dividing the initial and final prices by the minimum bid increment. This calculation not only helps simulate the sensation of acceleration in auctions but also reflects participants' psychological state and strategic choices during competition.

$$G_{\text{Auction}} = \frac{\min(F_{\text{Price}}, I_{\text{Price}})}{\Delta p} \tag{5.6}$$

$$T_{\text{Auction}} = \frac{\max(F_{\text{Price}}, I_{\text{Price}})}{\Delta p} \tag{5.7}$$

$$GR = \frac{\sqrt{G}}{T} = \frac{\sqrt{2\frac{\min(F_{\text{Price}}, I_{\text{Price}})}{\Delta p}}}{\frac{\max(F_{\text{Price}}, I_{\text{Price}})}{\Delta p}} \tag{5.8}$$

### 5.3.3 From Physical Models to Auction Modeling

After analyzing auction dynamics using physical analogies, we've gained insights into how core auction items impact the entire auction process, akin to gravitational effects observed in astrophysics. We use GR theory and dynamic pricing models to analyze price fluctuations and participant decisions more precisely [85]. Our study has revealed significant changes in auction speed surrounding core items, leading us to consider a "gravitational" influence on surrounding items. To explore this concept, we propose a unique analytical framework inspired by the three-body problem and its derivative, the "restricted three-body problem" in physics (Figure 5-1 and Figure 5-2, respectively).

Figure 5-1: The Three-Body Problem.[1]

Figure 5-2: The Restricted Three-Body Problem.[2]

[1]This figure was created by the author.
[2]This figure was created by the author.

Based on our analysis of actual auction data, we have observed significant changes in auction speed around core items, sometimes leading to neglect of other items due to insufficient bids. This phenomenon relates to specific astronomical dynamics, especially gravitational interactions[3]. We are considering whether some physics principles could explain similar phenomena in auctions. Specifically, the "restricted three-body problem" offers a unique perspective [95,96], where highly sought-after auction items significantly influence participants' behavior, impacting their decisions and neglecting other auction items. Therefore, we propose using this model as a framework to analyze auction dynamics. In the restricted three-body problem, if the mass of one of the objects (usually the third object) is very small, its gravitational influence on the other two main objects can be neglected. In this case, the third object is only influenced by the gravitational pull of the two main objects, while the two main objects move according to the solution of the two-body problem [97]. The main reasons for this choice include the following:

- **Moderate Complexity**: Compared to the binary star problem, the restricted three-body problem more precisely depicts the unilateral influence of one or more bodies on a smaller body, which aligns more closely with the reality of how core auction items influence participants in auctions.

- **Direct Analogy**: In the auction environment, participants often make decisions revolving around one or two core items, similar to how a small body is affected by the gravitational forces of two large bodies, making applying the model intuitively reasonable.

- **Theoretical Extensibility**: Employing this physical model provides a new perspective for analyzing known data and may also reveal patterns and relationships in auction behaviors that have not been observed before, offering new possibilities for theoretical and practical development.

[3]The "restricted three-body problem," which describes the influence of two large mass bodies (such as two major celestial bodies) on a third negligible mass body (such as a probe or small satellite).

The model examines how participants create their own "game mass" through decision-making and psychology, influencing the auction process. We aim to understand how high-value items shape auctions. Using the "restricted three-body value problem" framework, we can describe bidding interactions and determine which items have a significant market impact. Additionally, we will introduce the gravitational formula in the mind to analyze interactions between core auction items and participants.

#### 5.3.3.1 The Restricted Three-Body Problem

The restricted three-body problem serves as a metaphor for the dynamics observed in auctions, particularly in how participants' attention is distributed across different auction items. We conceptualize the auction process as a game where participants (players/bidders) move from one auction item to another, each involving a well-defined game process. This can be likened to a small spacecraft navigating past one celestial body after another. While individual participants' interest in items, capital amounts, and other factors may introduce variations in their 'game masses,' these factors are relatively insignificant compared to the 'game mass' generated by the auction process itself. As such, participants can be considered bodies of negligible game mass, with their behavior primarily influenced by the gravitational forces of the auction items.

Similarly, the game process of auction items with lighter game masses orbiting the core auction items is also influenced by the game mass of these core items. Attention plays a critical role in this dynamic, as human physiological limits dictate that participants can only focus on a finite number of items simultaneously [98]. When one item captures a participant's attention, the attention available for other items inevitably diminishes. By observing the 'game speed' of these auction items at different distances, we aim to understand how core auction items influence other items and gain insight into the changes in the attractiveness of auction items as perceived by participants throughout the auction process.

Having outlined the metaphorical framework of the auction process through the lens of the restricted three-body problem, we now shift our focus to a more concrete and quantifiable approach to understanding the gravitational forces within auctions. The need for a simplified yet powerful model to capture the essence of auction dynamics leads us to consider the principles of gravitational interaction not just as a metaphor but as a foundational element of our analytical toolkit. Thus, we introduce the 'Gravitational Formula in the Mind,' which directly draws from the universal law of gravitation, adapting its core principles to the context of auction dynamics. This approach allows us to move beyond qualitative analysis, providing a quantitative method to examine the influences and interactions that govern the auction process.

#### 5.3.3.2 Gravitational Formula in the Mind

Curiosity is an intrinsic drive for animals to explore the world, and rewards are simply a stimulus to action [99]. Therefore, participating in activities out of curiosity and finding them pleasurable is a natural feature of higher organisms such as humans [100]. This curiosity is driven by tangible rewards and an intrinsic desire to understand and interact with the world. What most easily arouses human curiosity is a surprise, a strong signal difference [101].

In auction bidding, the core auction item acts as the strongest signal, arousing the participants' curiosity and causing them to pay close attention to these items, even if they may not be able to bid on them. This heightened interest leads to deviations in participants' behavior, where they do not always follow the most economically valuable course of action and are willing to incur costs for these slightly less economical actions. We can even refer to this as the "cost of moving with the heart." These deviations affect auction dynamics in a way that can be analyzed using game refinement theory and the concept of "motion in the mind" [86]. It is feasible to study the irrational behaviors of participants in economic transaction environments using methods from game research that analyze player behavior. However, this requires the economic transaction scenarios to meet many conditions. Our extensive preliminary research has demonstrated its feasibility [85, 86].

Considering the characteristics of auction dynamics and the preliminary stage of our research, we chose to employ a simplified model analogous to the universal law of gravitation as our analytical tool. This decision is based on several key considerations:

**Intuitiveness and Simplicity**: The universal law of gravitation provides an intuitive and relatively simple way to describe the interaction between two objects, making the model easy to understand and implement. In the context of auctions, this model allows us to use “mass” (the attractiveness of the auction item) and “distance“ (the relationship between the item and the participants) as key variables to explore the influence of core auction items on the dynamics of the auction.

**Scalability and Adaptability**: Although the universal gravitation model is relatively simple in representation, it offers enough flexibility to adapt to various auction scenarios and dynamics. The model can be adjusted based on data availability and specific research needs, such as introducing additional variables or modifying the influence weights of existing variables.

**Bridging Theory and Empiricism**: By applying physics concepts to economics, our model provides a new perspective for auction theory and may also uncover patterns and relationships in empirical data that have not been noticed before. This interdisciplinary approach fosters theoretical innovation and lays the groundwork for further empirical research. Furthermore, it verifies the feasibility of this modeling direction and provides a foundational framework for future refinement using the latest mathematical tools, such as computational symplectic topology, Floer theory, and Lindstedt-Poincaré methods.

Although general relativity offers a more complex and comprehensive framework for describing gravitational effects, considering auction research's specific context and objectives, we believe adopting the universal gravitation model is a more reasonable choice. This approach enables us to effectively capture and analyze the core dynamics within auctions while maintaining manageability and clarity of analysis. To concretize this framework, we adopt the universal law of gravitation as the mathematical description of the interactions between core auction items and between items and participants. The formula is as follows:

$$\mathcal{F} = \mathcal{G}\frac{m_1 m_i}{r_i^2} \tag{5.9}$$

In our model, $\mathcal{F}$ represents the gravitational force between two auction items or the interaction force between an item and a participant; $\mathcal{G}$ is the gravitational constant, which in our model can be considered as an adjustment factor for the auction environment; $m_1$ and $m_i$ represent the "game mass" of two entities. In the context of auctions, $m_1$ specifically refers to the uncertainty a participant must overcome to acquire the core auction item, i.e., the "game mass" of the core auction item. Meanwhile, $m_i$ refers to the uncertainty a participant must overcome to acquire other auction items, such as auction item $i$, i.e., the "game mass" of the $i$. $r$ represents the distance between the two, which, in our model, signifies the gap between the order of appearance of two lots within the same auction.

$$r_i(\mathcal{F}) = \sqrt{\frac{\mathcal{G} m_1 m_i}{\mathcal{F}}} \tag{5.10}$$

By employing the aforementioned formula, our goal is to quantitatively assess the dynamic interactions between core auction items and other items during the auction process, thereby offering an effective tool for forecasting and elucidating changes in auction behavior. This approach extends our analysis beyond treating games as isolated single interactions, broadening the perspective to encompass a designed set of interrelated games.

### 5.3.4 Computational Modeling

In our research, we anchor the study into two pivotal segments. The first part involves determining the 'velocity' and 'mass' of each item in an auction event (Eq. (5.11)), drawn from the motion in mind concept [2]. Meanwhile, the second part introduces a theoretical framework that mirrors the law of universal gravitation to explore dynamic interactions during auctions. The goal is to measure the interactions between primary and ancillary auction items by identifying a 'gravitational constant' ($G$) in the auction game.

$$v = 1 - m = \frac{\max(F_{\text{Price}}, I_{\text{Price}})}{\min(F_{\text{Price}}, I_{\text{Price}})} \tag{5.11}$$

We utilized machine learning to analyze Christie's and Sotheby's auction data to comprehend the dynamics between auction items and participants. Through careful data processing and the application of machine learning techniques, we estimated the 'gravitational constant' ($\mathcal{G}$) and other factors influencing the interaction force ($F$). Our model measures the 'distance' ($r$) using temporal proximity, psychological association, or perceived valuation gap metrics. By applying the concept of gravity from physics to economics, we offer a unique perspective on auction markets. Our multidisciplinary approach allows us to understand auction mechanics and quantitatively predict behavioral changes within auctions. By integrating computational modeling with empirical data analysis, we unveil previously unexplored patterns and relationships, contributing to advancements in auction theory. MATLAB R2022b[4] was used for correlation analyses, and the general procedures of the proposed computational model are given as in Algorithm 2.

**Algorithm 2** Computational Model for Analyzing Auction's Gravitational Formula in the Mind

```
Input: Auction Data (𝒟) with Initial Price and Final Price for items
Output: Estimated parameters for Gravitational Model (𝒢, m, v, r)
Initialize: Choose a machine learning model ℳ
for each item i in 𝒟 do
    Calculate game mass m_i based on Initial Price and Final Price
    Determine game velocity v_i using 1 = m_i + v_i
end for
Preprocess data 𝒟 for ℳ
Feature Engineering to represent m, v, and r effectively
Fit model ℳ on 𝒟 to learn 𝒢
while not converged do
    Optimize ℳ to minimize error in predicting F
    Update 𝒢, m, v, and r based on model feedback
end while
Evaluate model ℳ performance
Analyze the importance of features (m, v, r) in predicting F
return 𝒢, m, v, r =0
```

We're introducing the importance score of auction items to refine our computational model and accurately reflect auction dynamics. This score is based on the

[4] https://www.mathworks.com/

intensity of the auction house's pre-auction promotions for items, especially how certain items are highlighted. We believe the greater the promotional efforts, the more influential and attractive the item is in the auction process. By analyzing pre-auction promotional materials, our model identifies each auction's core items and assigns weighted scores based on the intensity and scope of their promotions. This helps us identify the most important items in each auction and quantify their potential impact on auction behaviors and participant actions (Algorithm 3). The process proceeds as follows:

1. Analyze the promotional materials for each auction to determine the promotion intensity for each item and whether it is a cover item.

2. Based on the intensity of promotion and cover item status, allocate a preliminary importance score to each item.

3. Adjust the scoring mechanism to ensure the scores reflect the actual impact of the items on auction behaviors, which may involve further analysis of auction data to verify the relationship between scores and auction outcomes.

---

**Algorithm 3** Calculating the Importance Scores of Auction Items Based on Promotional Efforts

---

**Input**: Auction Items Data $\mathcal{I}$, Pre-Auction Promotional Materials $\mathcal{P}$
**Output**: Importance Scores for Each Auction Item
Initialize an empty list for importance scores $Scores$
**for** each item $i$ in $\mathcal{I}$ **do**
    Determine the promotion intensity $P_{intensity}$ for $i$ based on $\mathcal{P}$
    Determine if $i$ is featured as the cover $C_{feature}$ in $\mathcal{P}$
    Calculate a preliminary importance score $S_{prelim}$ for $i$ considering $P_{intensity}$ and $C_{feature}$
    $Scores[i] \leftarrow S_{prelim}$
**end for**
**for** each score $s$ in $Scores$ **do**
    Adjust $s$ based on additional insights from auction data to reflect actual impact on auction outcomes
**end for**
**return** $Scores$ =0

---

### 5.3.5 Experiment Design and Data Collection

We compiled a dataset from the contemporary art auction prices of Sotheby's and Christie's from 2020 to 2023. This dataset includes guide prices, exhibition estimates, and other relevant information from that period. Additionally, we selected representative cities from Asia, Europe, and America, specifically Hong Kong, London, and New York, for focused observation. For the purposes of this study, we tracked data from each auction item in these three cities from 2020 to 2023, with particular emphasis on the data of the first auction item and core auction items.

## 5.4 Research Innovations in Economic Games

This research contributes to the study of economic games by addressing critical gaps and introducing innovative approaches across three key dimensions:

### 5.4.1 Systematic Framework for Analyzing Complex Economic Behavior

Traditional economic research often adopts a "point-to-point" approach, addressing specific problems in isolation, which limits its ability to capture complex and irrational economic behaviors comprehensively. To address this challenge, we integrated *Game Refinement Theory* and the *Motion in Mind Framework*, originally developed for game behavior analysis, into economic transaction scenarios. This integration transitions the analysis to a "system-to-system" perspective, enabling a holistic understanding of behavior patterns and facilitating generalized problem-solving strategies. This methodological advancement broadens the applicability of these models to economic domains previously considered unsuitable for such analysis.

### 5.4.2 Quantitative Modeling of Non-Economic Utility

Conspicuous consumption often involves decisions driven by non-economic factors, such as social status and identity validation, which are difficult to capture within classical economic paradigms. By employing *Game Refinement Theory* and the *Motion in Mind Framework*, we developed a quantitative methodology to model and measure these non-economic utilities. This advancement illuminates the motivational forces behind consumer behavior and provides actionable insights for optimizing strategies in competitive economic settings, bridging the gap between qualitative theories and quantitative applications.

### 5.4.3 Audience Effects as a Quantifiable Behavioral Factor

The influence of audience presence on economic decisions, particularly in gamified scenarios and conspicuous consumption, is an underexplored yet crucial aspect of economic dynamics. This study systematically incorporates the audience as a core variable in behavioral modeling. By analyzing experimental data, we quantified the audience's impact on key behaviors, including bidding strategies and engagement levels. This contribution not only enriches theoretical models but also provides empirical evidence for understanding the social dynamics that underpin economic activities.

## 5.5 Analysis of the Starting Point in Auction Bidding ($I$ value Analysis)

The initial price in an auction, denoted as $I$, represents the lowest bid accepted to start the bidding process and serves as a critical starting point that can shape the auction's trajectory. When set strategically, it can create a competitive environment, heightening participant engagement as bidders perceive the value and scarcity of the items differently. Auction houses determine this initial price through a multidimensional analysis of the item's rarity, demand, condition, and historical significance, aiming to balance attracting potential buyers and protecting the seller's interests.

Our collected auction data, as illustrated in Figure 5-3 and Figure 5-5, shows that 95.63% of initial prices are set below the lower limit of the estimated value, $I < E_{\mathrm{L}}$; 1.36% exactly match the lower limit of the estimated value, $I = E_{\mathrm{L}}$; 2.56% exceed the lower limit but are below the upper limit of the estimated value, $E_{\mathrm{L}} < I < E_{\mathrm{U}}$; and in 0.45% of cases, the auction house did not provide an estimated value. It is particularly noteworthy that, during Christie's Spring 2022 auction, there was a unique instance where the initial price was set above the upper limit of the estimated value, marking this as the only occurrence of such an event, $E_{\mathrm{U}} < I$. In this exceptional case, the auction velocity was recorded at $v \approx 0.20$ , with $N$ valued at 5.13.

### 5.5.1 $I < E_{\mathrm{L}}$

Figure 5-4 illustrates the distribution of $N$ values under the condition $I < E_{\mathrm{L}}$. The horizontal axis indicates the item number in each auction, and the vertical axis represents the corresponding $N$ values. Notably, 98.5% of the $N$ values fall within the range $[1, 9]$, indicating a highly concentrated distribution. Extreme cases are primarily observed in the first item and the main promotional item of each auction. When extreme cases are excluded, the average $N$ value across auctions is calculated to be 2. This suggests that auctions are highly skill-intensive, as lower $N$ values typically require precise decision-making.

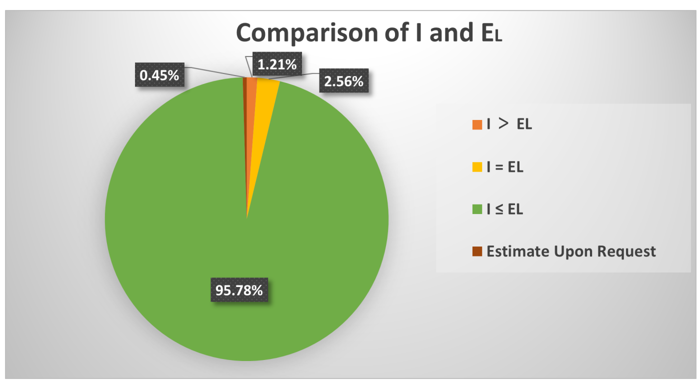



Figure 5-3: Comparison of $I$ value and $E$ value lower limit

### 5.5.2 $I > E_{\mathrm{L}}$

Although in auction data statistics, the case of $I > E_{\mathrm{L}}$ occurs less frequently, their occurrence is quite regular. As shown in Figure 5-5, 40% of the $I > E_{\mathrm{L}}$ cases appear at the beginning of the auction; 40% of the $I > E_{\mathrm{L}}$ cases occur in the last few items

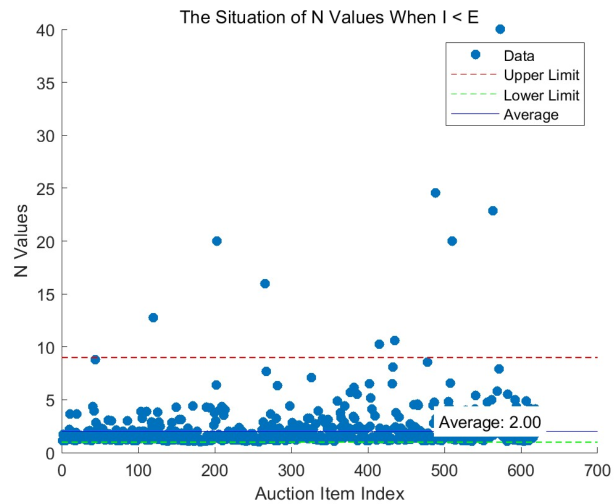



Figure 5-4: The situation of N value when $I < E$

of the entire auction but generally not in the very last item; and the remaining 20% occur in the middle of the auction.

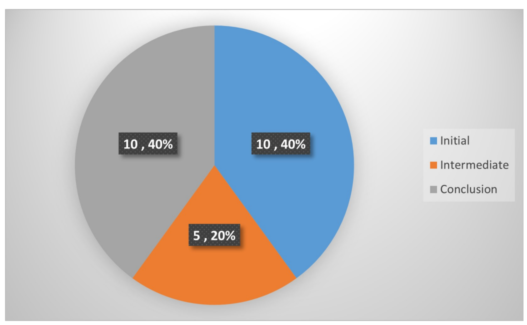



Figure 5-5: $N$ values when $I \leq E$

Due to the possibility of changing auctioneers midway through an auction, if we conduct a statistic based on one auctioneer being responsible for one auction, we can find that for all cases where $I \geq E_L$, including the values of $v$, $N$, and $\sqrt{N}$ (Table 5.1). When $I > E_{\mathrm{L}}$ occurs at the very beginning of the auction, the auction's $v$ value is significantly smaller compared to when $I < E_{\mathrm{L}}$. When $I > E_{\mathrm{L}}$ occurs in the final stages of the auction, the auction's $v$ value is generally higher, but the $N$ value does not appear outside the main range of $N$ values when $I < E_{\mathrm{L}}$, $N \in [1, 9]$.

Most interestingly, the 59th item in Christie's 2022 Hong Kong Spring Auction, where the starting price was twice the lower estimate, even higher than the upper estimate. However, its auction $v$ value and $N$ value indicate that it aligns with the game attractiveness of other cases where $I < E_{\mathrm{L}}$. This situation occurs because after the auction house announces the auction estimates and before the official start of the auction bidding, information that influences the auction item's price appears and is widely disseminated in the market. This hypothesis can also explain the data in the middle 20% of the auctions, where the $v$ and $N$ values are consistent with those in cases where $I < E_{\mathrm{L}}$.

Table 5.1: $N$ Values When $I \leq E$ for Christie & Sotheby

| **Auction House** | **Dates** | **Cite** | **Lot** | **Stage of Auction** | % | $v$ | $N$ | $\sqrt{N}$ |
|---|---|---|---|---|---|---|---|---|
| Christie | 2023 A | HK | 18 | Concluding | 100% | 0.5 | 2.00 | 1.41 |
| Christie | 2023 A | HK | 19 | Concluding | 100% | 0.5 | 2.00 | 1.41 |
| Christie | 2023 A | HK | 21 | Concluding | 100% | 0.5 | 2.00 | 1.41 |
| Christie | 2023 A | LDN | 49 | Concluding | 100% | 1 | 1.00 | 1.00 |
| Christie | 2023 A | LDN | 56 | Concluding | 100% | 0.72 | 1.39 | 1.18 |
| Christie | 2023 A | LDN | 59 | Concluding | 100% | 0.33 | 3.03 | 1.74 |
| Sotheby | 2023 | HK | 2823 | Intermediate | 125% | 0.83 | 1.20 | 1.10 |
| Sotheby | 2023 | HK | 2837 | Initial | 100% | 0.45 | 2.22 | 1.49 |
| Sotheby | 2023 | HK | 1201 | Initial | 100% | 0.31 | 3.23 | 1.80 |
| Sotheby | 2023 | NY | 3 | Initial | 100% | 0.27 | 3.70 | 1.92 |
| Sotheby | 2023 | NY | 8 | Initial | 100% | 0.35 | 2.86 | 1.69 |
| Christie | 2022 A | HK | 4 | Initial | 100% | 0.57 | 1.75 | 1.32 |
| Christie | 2022 A | HK | 47 | Conclusion | 100% | 0.38 | 2.63 | 1.62 |
| Christie | 2022 S | HK | 59 | Conclusion | 200% | 0.2 | 5.00 | 2.24 |
| Christie | 2021 A | HK | 1 | Initial | 107% | 0.2 | 5.00 | 2.24 |
| Christie | 2021 A | HK | 15 | Intermediate | 100% | 0.3 | 3.33 | 1.83 |
| Christie | 2021 A | HK | 18 | Intermediate | 138% | 0.39 | 2.56 | 1.60 |
| Christie | 2021 A | HK | 23 | Intermediate | 130% | 0.12 | 8.33 | 2.89 |
| Christie | 2021 A | HK | 33 | Intermediate | 117% | 0.67 | 1.49 | 1.22 |
| Christie | 2021 A | HK | 76 | Conclusion | 100% | 0.38 | 2.63 | 1.62 |
| Christie | 2021 S | HK | 1 | Initial | 100% | 0.14 | 7.14 | 2.67 |
| Christie | 2021 S | HK | 2 | Initial | 150% | 0.23 | 4.35 | 2.09 |
| Christie | 2021 S | HK | 8 | Initial | 100% | 0.27 | 3.70 | 1.92 |
| Christie | 2021 S | HK | 20 | Intermediate | 100% | 0.33 | 3.03 | 1.74 |
| Christie | 2021 S | HK | 41 | Initial | 125% | 0.14 | 7.14 | 2.67 |

A: Autemn; S: Spring; HK: Hong Kong; LON: London; NY: New York

The auction house sets the initial bid price ($I$) and considers the importance of auction velocity ($v$ value) for participants. The $v$ value reflects the level of competition in the auction and influences participants' perceptions of the competition and the event's attractiveness. When the $v$ value is low, the game is highly competitive, making it harder for competitors to win. Increased competitiveness makes watching the auction more engaging for observers, potentially drawing more potential competitors to join. Active competitors and observers use attention, which tends to decrease over time, according to Daniel Kahneman's "Attention and Effort" [102] and neurophysiological research [103].

When setting bid prices for auction items, beginning with a low $v$ value or introducing a new auctioneer is beneficial for two reasons. First, it draws in more observers, potentially turning them from passive spectators into active participants. Second, engaging in a challenging competition at the auction's beginning helps focus the competitive drive when participants have ample energy, making it easier to complete the task. In English auctions, luxury items such as artworks are sold, and participating in these auctions can be seen as a form of "conspicuous consumption" [25]. This situation means buyers may be motivated to publicly display their wealth and social status by bidding on these items. Auction houses should organize a highly competitive auction at the beginning with a reasonable starting price to attract attention and increase the perceived value of winning. However, towards the end of the auction, bidders may prefer to acquire items with less effort, meaning that a faster auction pace may be more suitable in this context.

Auction theory provides insights into how auction houses can achieve a lower auction velocity ($v$), defined as the ratio of the initial price ($I$) to the final price ($F$). This can be accomplished by minimizing $I$ or maximizing $F$, with a strong negative correlation between auction velocity and the Price Deviation Value. In English auctions, participants enter with private valuations that inform their bidding strategies, creating an environment where expected bidding prices are objectively present, rooted in individual assessments of worth [9].

The auction process follows a Bayesian mechanism, with participants adjusting their bids based on private valuations and observed behavior. This leads to a Nash equilibrium where the winning bid exceeds the second-highest valuation by the smallest allowable increment. This equilibrium reflects the strategic interplay among bidders, consistent with Bayesian Nash equilibrium principles in competitive bidding environments [7].

While final prices in auctions are influenced by bidders' financial constraints and private valuations, their distribution exhibits a discernible pattern. This regularity stems from the collective impact of individual financial capabilities and valuations across the participant pool. The structured distribution of final prices is an inherent characteristic of auction markets [30], reflecting the systematic convergence of bidders' private valuations and financial limitations. Consequently, although final prices remain uncertain until the auction concludes, their distribution follows a pattern objectively determined by the interplay of bidders' valuations and financial resources rather than being arbitrarily influenced.

### 5.5.3 Analysis of the Positions of $I$, $F$ and Auction Estimates

A preliminary analysis of the positions of Initial Price ($I$), Final Price ($F$), Estimate Lower ($E_L$), and Estimate Upper ($E_U$) values can offer insights into the auction dynamics, as illustrated in Figure 5-6.

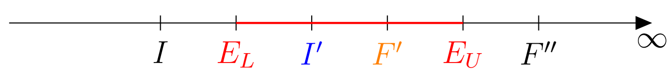



Figure 5-6: Auction dynamics based on the positioning of $I$, $F$, $E_L$, and $E_U$ values

- **Case 1: Accurate Estimate Range with $I < E_\mathbf{L}$ and $F \in [E_\mathbf{L}, E_\mathbf{U}]$**

  If the auction house's published estimates are accurate, meaning the estimate range meets the public expectations, i.e., Common Values $\in [E_\mathrm{L}, E_\mathrm{U}]$, and the initial price is below the lower limit of the estimate ($I < E_\mathrm{L}$). Then, the $F$ depends on the second highest bidder's Private Values, i.e., the minimum between the bidder's Maximum Willingness to Pay (MWP) and the Purchasing Power Limitation (PPL), $\min(\mathrm{MWP}, \mathrm{PPL})$. When the accurate estimate predicts the actual transaction price, i.e., $F$ falls within the estimate range, $F = F'$ and $F \in [E_{\mathrm{L}}, E_{\mathrm{U}}]$. It follows that $v_1 = \frac{I}{F'}$ with $\frac{I}{E_{\mathrm{L}}} \leq v_1 \leq \frac{I}{E_{\mathrm{U}}}$.

- **Case 2: Accurate Estimate Range with High Bidder's Private Value, $I < E_{\mathbf{L}}$ and $F > E_{\mathbf{U}}$**

  In the second case, while the auction house's estimate range is accurate with$I$ value suggesting $I < E_{\mathrm{L}}$, the bidder's private value, influenced by additional information, is higher. When the second highest bid exceeds$E_{\mathrm{U}}$, resulting in $F > E_{\mathrm{U}}$ as illustrated in Figure 5-6 as $F''$, where $F = F''$. This leads to $v_2 = \frac{I}{F''}$ and $v_2 \geq \frac{I}{E_{\mathrm{U}}}$, clearly indicating $v_2 > v_1$.

- **Case 3: Influence of New Information before Auction, $I > E_{\mathbf{L}}$ and $F \in [E_{\mathbf{L}}, E_{\mathbf{U}}]$**

  In the third scenario, influenced by new information received before the auction bidding or by intentional design by the auction house, $I > E_{\mathrm{L}}$ (denoted as $I = I'$), and if the estimate range is accurate, i.e., the market's common values fall within $[E_{\mathrm{L}}, E_{\mathrm{U}}]$ as shown in Figure 5-6 as $F'$, where $F = F'$. Consequently, $v_3 = \frac{I'}{F'}$. If $I' = E_{\mathrm{L}}$, then $v_3 = \frac{I'}{F'} \leq \frac{E_{\mathrm{L}}}{E_{\mathrm{U}}}$. If $I' > E_{\mathrm{L}}$, then $v_3 = \frac{I'}{F'} \geq \frac{E_{\mathrm{L}}}{E_{\mathrm{U}}}$, and $v_3 > v_2$.

- **Case 4: Changes in Common Values or Underestimated Auction House Estimates, $I > E_{\mathbf{L}}$ and $F > E_{\mathbf{U}}$**

  In the fourth case, common values change due to new information in the market, or the auction house's estimate range is significantly below market expectations, leading to $I = I'$ and $F = F''$. In this scenario, $v_4$ can vary, but it is certain that $v_4 < v_3$.

In Cases 1 and 3, when $F = F'$, the length of the auction game is restricted to 2-3, demanding high skill. In Cases 2 and 4, where $F = F''$, the restriction is removed, allowing for a potential increase in $N$, implying decreased skill. However, bidders can still make incorrect decisions, leading to financial losses.

An auction house can consider two approaches to designing an auction with a lower initial value ($v$). One approach is to select an item with a significantly higher final price ($F$) and start the auction with an initial value ($I$) below public expectations. This method has the advantage of being direct, but it may be too obvious for auction participants. Another approach involves announcing an estimated range below public expectations before the auction to increase the Price Deviation Value. This method uses a financial strategy called "Money on the table," which refers to unexploited profit opportunities in trading or investing. It describes gains that investors have not acted upon [104], indicating that the asset may be undervalued.

When you buy these assets, it seems like a safe move. However, you're taking a risk if you announce a lower estimate before an auction. This could force the auction to start bidding at a higher price ($I \geq E_{\mathrm{L}}$). If an auction house chooses the first strategy, it will not manipulate the published estimate but will select an item with a much higher final price to set as the starting auction bid. Most initial prices fall between 60% to 90% of the lower estimate limit, making up 81.15% of the total data (see Figure 5-7). Initial prices significantly lower than the lower estimate limit only account for 7.24%. This suggests that auction houses do not commonly use the first strategy.

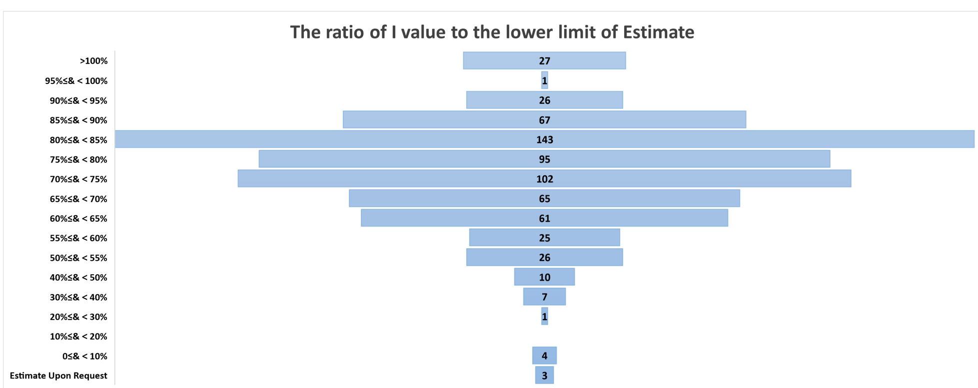



Figure 5-7: The ratio of I value to the lower limit of Estimate

It's tough to identify the second strategy in the data. Extreme cases in the overall data, where the $v$ value is smaller and the $N$ value is larger, indicate the potential for this phenomenon. The first strategy directly impacts the initial price but is rarely used in auction data. The second strategy subtly influences auction outcomes by potentially increasing engagement and generating larger $N$ values. It uses the "Money on the table" concept to make the auction more appealing without overtly lowering the initial price.

## 5.6 Results and Discussion

### 5.6.1 Estimation of the Gravitational Constant

The term "core auction items" refers to the most essential and desirable items featured in an auction, such as rare artworks, antiques, unique jewelry, and historical artifacts. These items attract the most attention and the highest bids at the event. Auction houses meticulously evaluate and select core items based on their rarity, provenance, historical significance, condition, and market demand. By carefully curating standout items, auction houses create a focal point that stimulates competitive bidding, enhances the auction's atmosphere, and contributes to its success.

Auction houses often highlight certain items as the main attractions, assuming that these will be the focal point of interest. However, the bidding dynamics may reveal that other items possess a more compelling allure to participants, indicating hidden appeal. This research evaluates core auction items using the concept of 'game mass.' We analyzed a dataset from multiple auctions to study bidding behaviors (see Table 5.2). The dataset includes various types of auction items. We evaluated auction houses' focus based on pre-auction promotions and feature presence and calculated importance scores.

Table 5.2: Importance Scores of Auction Items Based on Promotional Efforts

| **Auction No.** | **House** | **City** | **Sessions** | **Remark** | **Lot No.** | **IP** | **FP** | **Min Bid** | **BID** | $m$ | $v$ | $N$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | C | HK | First half | Cover | 11 | 90,000,000 | 160,000,000 | 10,000HKD | 11 | 0.44 | 0.56 | 1.78 |
| | | | First half | - | 15 | 50,000,000 | 65,000,000 | 10,000HKD | 4 | 0.23 | 0.77 | 1.30 |
| | | | Second half | - | 33 | 30,000,000 | 42,000,000 | 10,000HKD | 4 | 0.29 | 0.71 | 1.40 |
| 2 | C | LON | First half | Cover | 16 | 3,200,000 | 5,350,000 | 1,000GBP | 16 | 0.40 | 0.60 | 1.67 |
| | | | First half | - | 32 | 4,500,000 | 6,700,000 | 1,000GBP | 14 | 0.33 | 0.67 | 1.49 |
| | | | First half | - | 34 | 500,000 | 590,000 | 1,000GBP | 5 | 0.15 | 0.85 | 1.18 |
| 3 | C | NY | 20th Century | Cover | 35 | 52,000,000 | 64,000,000 | 10,000USD | 7 | 0.19 | 0.81 | 1.23 |
| | | | 20th Century | - | 14 | 20,000,000 | 25,000,000 | 10,000USD | 5 | 0.20 | 0.80 | 1.25 |
| | | | 20th Century | - | 12 | 35,000,000 | 45,000,000 | 10,000USD | 5 | 0.22 | 0.78 | 1.29 |
| 4 | S | NY | Now | Cover | 9 | 7,000,000 | 9,000,000 | 10,000USD | 4 | 0.22 | 0.78 | 1.29 |
| | | | Now | - | 4 | 7,000,000 | 9,200,000 | 10,000USD | 7 | 0.24 | 0.76 | 1.31 |
| | | | Now | - | 7 | 5,500,000 | 9,500,000 | 10,000USD | 25 | 0.42 | 0.58 | 1.73 |
| 5 | S | NY | Contemporary | Cover | 129 | 32,000,000 | 39,000,000 | 10,000USD | 8 | 0.18 | 0.82 | 1.22 |
| | | | Contemporary | - | 105 | 8,000,000 | 16,000,000 | 10,000USD | 27 | 0.50 | 0.50 | 2.00 |
| | | | Contemporary | - | 125 | 21,000,000 | 27,500,000 | 10,000USD | 8 | 0.24 | 0.76 | 1.31 |
| 6 | S | LON | Now | Cover | 10 | 280,000 | 390,000 | 1,000GBP | 6 | 0.28 | 0.72 | 1.39 |
| | | | Now | - | 7 | 1,700,000 | 2,500,000 | 1,000GBP | 6 | 0.32 | 0.68 | 1.47 |
| | | | Now | - | 11 | 900,000 | 2,100,000 | 1,000GBP | 14 | 0.57 | 0.43 | 2.33 |
| 7 | S | LON | Contemporary | Cover/PASS | 109 | 11,000,000 | 14,500,000 | 1,000GBP | 8 | 0.24 | 0.76 | 1.32 |
| | | | Contemporary | - | 103 | 500,000 | 600,000 | 1,000GBP | 5 | 0.17 | 0.83 | 1.20 |
| | | | Contemporary | - | 101 | 450,000 | 800,000 | 1,000GBP | 8 | 0.44 | 0.56 | 1.78 |
| 8 | S | HK | Modern | Cover | 2814 | 28,000,000 | 36,000,000 | 10,000HKD | 5 | 0.22 | 0.78 | 1.29 |
| | | | Modern | - | 2813 | 8,500,000 | 12,000,000 | 10,000HKD | 6 | 0.29 | 0.71 | 1.41 |
| | | | Modern | - | 2830 | 9,500,000 | 13,500,000 | 10,000HKD | 7 | 0.30 | 0.70 | 1.42 |
| 9 | S | HK | Contemporary | Cover | 1208 | 45,000,000 | 71,000,000 | 10,000HKD | 7 | 0.37 | 0.63 | 1.58 |
| | | | Contemporary | - | 1206 | 48,000,000 | 61,000,000 | 10000HKD | 5 | 0.21 | 0.79 | 1.27 |
| | | | Contemporary | - | 1211 | 24000000 | 32000000 | 10,000HKD | 6 | 0.25 | 0.75 | 1.33 |

Note:- C: Chrisitie; S: Sotheby; HK: Hong Kong; LON: London; NY: New York; Min Bid: minimum bid price;

### 5.6.2 Consistency across Different Auctions

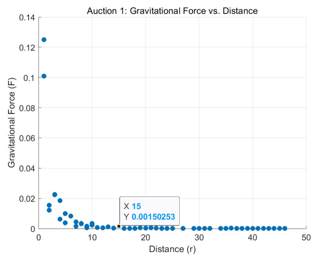
The gravitational model was used in nine auction sessions by Christie's and Sotheby's worldwide. Using a nonlinear least squares estimation in MATLAB R2022b, we optimized the gravitational constant ($\mathcal{G}$) to match observed forces. Our analysis consistently yielded gravitational constants around 1.0 (Table 5.3), confirming the model's reliability. The maximum distance ($r$) where significant forces ($\mathcal{F}$) were detected aligns with theoretical expectations, validating the model's accuracy in depicting the influence range of core auction items.

Table 5.3: Summary of Gravitational Constants across Auctions

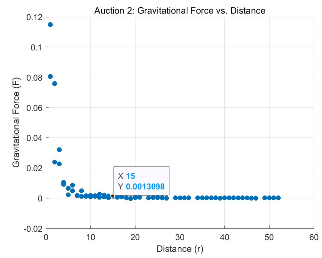
| **House** | **City** | **Century** | **Sessions** | **$\mathcal{G}$ Value** |
|---|---|---|---|---|
| Christie's | Hong Kong | 20th/21st | 57 | 1.0482 |
| Christie's | New York | 20th | 65 | 1.0276 |
| Christie's | London | 20th/21st | 68 | 0.9722 |
| Sotheby's | London | Now | 22 | 0.8801 |
| Sotheby's | New York | Now | 19 | 0.9319 |
| Sotheby's | Hong Kong | Modern | 39 | 0.9928 |

The graphical representations (Figures 5-8, Figures 5-9 and Figures 5-10) visually corroborate these findings, depicting the declining influence with increased distance from the core auction items, which is consistent with the gravitational pull observed in physical systems. This analysis validates our computational model and enhances our understanding of the dynamic interplay at auctions. It confirms that the core item significantly influences the auction pace, akin to a gravitational pull in physical systems.

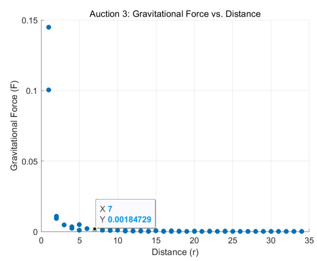
The placement and timing of core auction items can significantly impact the dynamics of the auction process across different formats. In English auctions, bidders focus on each item, while in Dutch auctions, attention can shift dramatically due to high-interest core items. Our research shows that attention dynamics in Dutch auctions can be manipulated to enhance participant engagement, even in auctions not associated with luxury goods. To study the dynamics, we used $v = 1 - m$ and $N = \frac{1}{v}$ to quantify how strategic item placement affects auction velocity. Data for




(a) Chrisitie HK

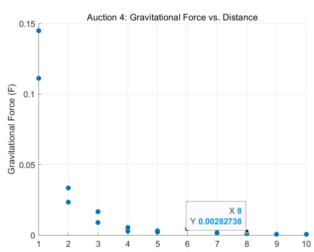



(b) Chrisitie LON

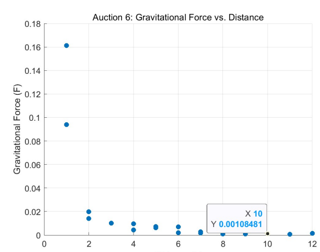



(c) Chrisitie NY

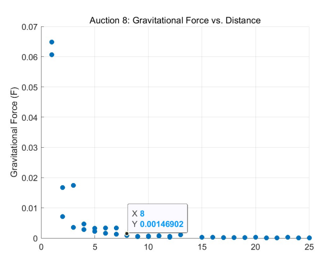
Figure 5-8: Chrisitie 20th/21st century Auctions 2023: Hong Kong (a), London (b), and New York (c)




(a) Sotheby HK Now

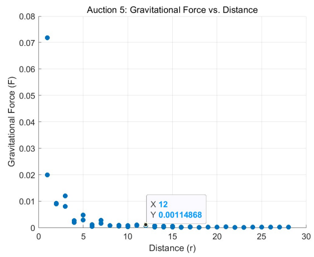



(b) Sotheby LON Now

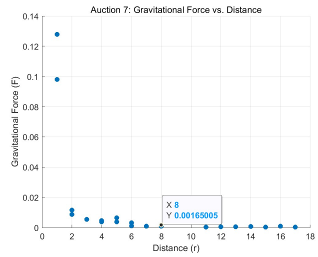



(c) Sotheby NY Modern

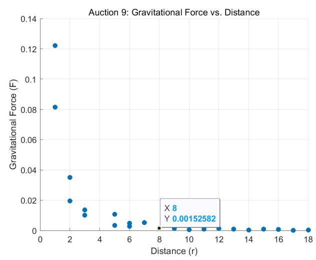
Figure 5-9: Sotheby Now or Modern Auctions 2023: Hong Kong(a), London(b), and New York(c)




(a) Sotheby HK Contemporary




(b) Sotheby LON Contemporary




(c) Sotheby NY Contemporary

Figure 5-10: Sotheby Contemporary Auctions 2023: Hong Kong(a), London(b), and New York(c)

the Dutch auction study came from the Kunming Flower Auction Center.

Our research is somewhat limited due to the lack of publicly available data, but we plan to collect more and conduct further in-depth studies. The Dutch auction involves flowers of all grades, with nine clocks at the auction site representing the prices of auction items. We aim to make an exciting discovery by arranging the N values of rose auctions of grades A, B, and C chronologically.

In position 36, the value of $N$ for Grade B becomes large, while for Grade C, it drops to nearly zero at this position and the following ones. This is because the 36th item of Grade A, named ‘Suxing,’ is the star of the day, capturing the attention of all bidders. In “Attention and Effort,” Daniel Kahneman [102] discusses the interference that occurs when performing two tasks simultaneously. Research shows that participants have the freedom to decide which task is more disrupted. This exemplifies the principle of selective allocation of cognitive resources, allowing individuals to adjust attention based on task priority and complexity. This study validates the limitations of the human capacity to process multitasking information,

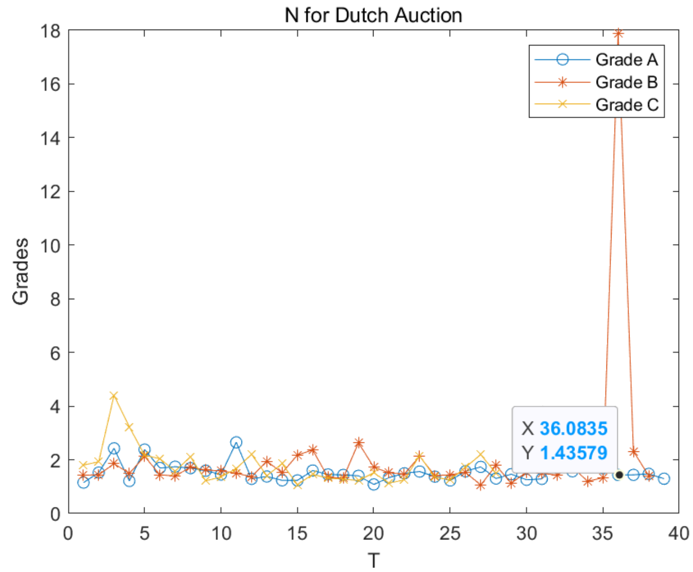



Figure 5-11: The dynamics of velocity from the Dutch auction Grade C

as in the cognitive load theory, and emphasizes the importance of selective attention allocation in executing complex tasks.

In Dutch auctions, participants' attention can influence the auction's pace and final price, ultimately affecting the transaction. Winning bidders can attract attention from others, increasing the perceived value of their purchases. This highlights the importance of attention in auctions as both a cognitive resource and a strategic asset for enhancing social status. Capturing and maintaining attention not only impacts the auction's outcome but also serves as a form of social signaling.

As analyzed previously, the results show that core auction items act as gravitational centers in both English auctions (Figures 5-8, 5-9) and Dutch auctions (Figure 5-10). The influence of core auction items decreases as the distance between items increases, consistent with the plotted data. This phenomenon arises because core auction items capture the attention of participants and observers alike.

When audiences notice core auction items **before the auction**, their interest in these items can motivate them to attend the auction, even if they lack the financial capacity to bid on the core items. This attention can lead them to explore other auction items during pre-auction exhibitions, thereby converting potential participants into active bidders.

Alternatively, when audiences notice core auction items **during the auction**, especially in online settings, the visibility of these items can enhance their prominence and elevate the non-economic rewards for the winning bidders, such as social recognition and prestige.

However, another scenario, as depicted in Figures 5-8, 5-9, and 5-10, reveals that when participants already engaged in the auction shift their focus from other items to core items, the game mass of the core item draws attention away from other auction items. This reallocation of cognitive resources can reduce competition for non-core items, highlighting the strategic importance of:

1. Promoting core auction items effectively.

2. Designing complementary item combinations.

3. Optimizing the placement of core items within the auction sequence.

To further explore these dynamics, I developed a simulation model, *"Attention Shift Simulation due to Core Items,"* as part of this research. This model illustrates how core items concentrate participant attention and provides a computational framework for optimizing auction dynamics. Combined with other simulation components, it contributes to a comprehensive analysis of auction behaviors. Such techniques and strategies form the foundation for designing customer flows in virtual marketplaces, contributing to both academic research and practical applications in digital economies.

The following algorithm demonstrates a computational framework of the proposed simulation model:

### 5.6.3 Comparative Analysis of Auctions to Other Games

Auction scenarios present a unique blend of economic and game-like characteristics, making them stand out among various financial transactions. While many economic activities inherently possess elements of game dynamics, auctions are particularly well-suited for analysis due to their well-defined rules, accessible data, and the clear

**Algorithm 4** Attention Shift Simulation due to Core Item

InputInput OutputOutput coreItem: Identified core auction item auctionData[year_start : year_end]: Data of auction items AI_attentionShift: Modeled changes in attention for each item

coreItemInfluence ← calculateCoreItemImpact(coreItem) item in auctionData distanceToCoreItem ← calculateDistance(coreItem, item) distanceToCoreItem = 0 AI_attentionShift[item] ← maxAttentionImpact(coreItemInfluence)

AI_attentionShift[item] ← coreItemInfluence / (distanceToCoreItem$^2$) **return** AI_attentionShift

temporal boundaries of their competitive interactions. This distinctiveness allows for more precise measurement and comparison. To better understand the game-like nature of auctions, we compare them to other games and competitive sports, identifying key metrics that define their game utility and economic significance.

To accurately capture the game-like nature of auctions and compare them to other competitive activities, we utilize two key metrics: game velocity ($v$) and game mass ($m$). Game velocity ($v$) measures the speed at which the auction progresses, influencing how participants perceive the pace and urgency of the competition. Game mass ($m$), on the other hand, reflects the complexity or challenges inherent in the auction, affecting the difficulty the participants face. By applying these metrics, we can quantitatively assess the dynamic characteristics and engagement levels of auctions concerning other games and sports. Table 5.4 presents this comparative analysis, highlighting how auctions align and diverge from other forms of competitive interactions. Comparative analysis of various games and auction scenarios using the metrics $v$ (game velocity) and $m$ (game mass) reveals generally, prices lower to participant engagement and challenge levels across different domains.

Our results indicate substantial differences in $m$, $v$, and $N$ values between the first auction item and the rest of the auction. In traditional games, a higher game velocity or smaller game mass makes the game feel more thrilling, while a slower game velocity makes the task feel more challenging and skill-intensive. However, in auctions, participants experience both "game stimulation" (game velocity) and "economic stimulation." The first auction item, typically chosen by the auction house, is generally priced lower than the average. This creates a psychological bias among

Table 5.4: Various analysis of games using $v$ and $m$ compared to auction

| **Category** | **Game** | **v** | **m** |
|---|---|---|---|
| **Board Games** | Chess | 0.22 | 0.78 |
| | Shogi | 0.35 | 0.65 |
| | Go | 0.60 | 0.40 |
| **Sports** | Soccer | 0.11 | 0.89 |
| | Badminton | 0.58 | 0.42 |
| | Basketball | 0.27 | 0.73 |
| | Table tennis | 0.50 | 0.50 |
| **Major Public Gambling** | Online casino | 0.96 | 0.04 |
| | Pachinko/Pachislot | 0.85 | 0.15 |
| | Horse race | 0.80 | 0.20 |
| | Speedboat race | 0.75 | 0.25 |
| | Bicycle race | 0.75 | 0.25 |
| | Auto race | 0.70 | 0.30 |
| | Lottery | 0.46 | 0.54 |
| **English Auction** | Average Data | 0.67 | 0.33 |
| | The First Lot | 0.28 | 0.72 |
| | Core auction items | 0.71 | 0.29 |

participants, making them believe their bidding skills are superior.

The first auction item exhibits a significantly higher $m$ value (0.72) than the average for all items (0.33), reflecting more intense competition and increased bidder engagement. This scenario resembles skill-based games like chess, where higher $m$ values demand more significant expertise. By starting with challenging items, auction organizers can stimulate activity, leveraging the principle that scarcity increases perceived value and status—a concept we call "Game Incentives." Strategically, the first auction item functions like bait fishing, where an attractive but challenging item draws participants' interest. This item creates an anchor point in participants' mental accounting, influencing their bidding behavior and willingness to pay. To better understand this process, we have developed a dynamic decision-making model.

### 5.6.4 Bidder Decision Dynamics Model

Based on our study, the final bid price depends on the relationship between the maximum amount a bidder is willing to pay (MWP) and their purchasing power limit (PPL). Meanwhile, the willingness of a bidder to pay is influenced by two main factors: the item's personal valuation (PV) and the potential for social status enhancement (SV). The formula is given by Eq. (5.12) and Eq. (5.13), respectively.

$$\text{Final price} = \min(\text{PPL}, \text{MWP}) \tag{5.12}$$

$$\text{MWP} = \alpha \times \text{PV} + \beta \times \text{SV} \tag{5.13}$$

The PV represents the personal valuation of the item, reflecting the bidder's intrinsic value judgment. Meanwhile, the SV represents the potential for social status enhancement, indicating the bidder's desire to elevate their social status by winning the auction. Finally, $\alpha$ and $\beta$ are parameters that modulate the impact of PV and SV. The bidder's willingness to pay is not static but dynamically adjusts with new information. Then, the updated MWP is expressed as Eq. (5.14), where $\gamma$ represents the sensitivity to new information, reflecting how much new information influences the bidder's decision.

$$\text{MWP}_{\text{new}} = \text{MWP} + \gamma \times \text{New information impact} \tag{5.14}$$

Subsequently, to accurately simulate bidder behavior, we consider changes in purchasing power using the relationship based on Eq. (5.15). The $\Delta F_P$ represents the change in purchasing power, reflecting fluctuations in the bidder's purchasing power during the auction, $\Delta v$ represents the rate of change of purchasing power, describing the speed of purchasing power change, $I_P$ represents the initial purchasing power at the start of the auction, and $F_P$ represents the final purchasing power at the end of the auction.

$$\Delta F_P, \Delta v = \frac{I_P}{\Delta F_P} \tag{5.15}$$

In auctions, when the inflation rate change ($\Delta F_P$) exceeds the inflation rate ($F_P$), the change in the item's value ($\Delta v$) is less than its initial value ($v$), indicating increased purchasing power urgency. This model is crucial for developing accurate auction bidding simulations, combining static and dynamic bidder behaviors. It also influences participants' perception of game difficulty and their engagement through psychological manipulation, significantly improving the overall effect and participant satisfaction.

The most valuable items in auctions, known as core auction items, are essential for keeping participants engaged. These items have high perceived value and attractiveness ($v = 0.71$), similar to high-stakes games, motivating bidders to win. In English auctions, core items are usually luxury goods, while in Dutch auctions, competitors bid on expensive core items to showcase their prowess and capabilities [25, 105]. Observers at the auction, who are potential bidders, may not have the financial capacity to bid on core auction items. The attention and competition attracted by core auction items divert observers' focus. This issue becomes more pronounced in Dutch auctions, affecting the success of other items being sold simultaneously.

Furthermore, core auction items serve as a draw during the pre-auction exhibition period. Many potential bidders who initially ignored the auction started to take interest due to the core auction items. They pay the deposit to participate in the auction but lack the financial strength to win the core auction item. Therefore, core auction items play a significant role in driving overall auction revenue. Such phenomenon can be examined from the behavior of auction spectators [86].

## 5.7 Chapter Conclusion

This study has explored the intricate relationship between game dynamics and customer experience (CX) design within auctions, mainly by applying psychological principles such as the Serial Position Effect and the Peak-End Rule. Our findings highlight the significant role of attention in auction environments, where economic and non-economic factors drive participant behavior. By strategically positioning auction items and carefully timing their introduction, auction houses can create a more engaging and satisfying experience, thus optimizing the overall auction process.

Furthermore, our research underscores the dual nature of utility in auctions—where participants are influenced by economic utility and "game utility." This concept reflects the psychological and social motivations that drive behavior in competitive environments like auctions, where factors such as identity, social status, and enjoyment play a crucial role. These insights broaden our understanding of decision-making processes, revealing the limitations of traditional economic models that focus solely on rational behavior.

While this analysis offers valuable perspectives, it is vital to acknowledge the limitations, including the focus on specific auction types and the lack of real-time bidding data. Future research could build on these foundations by exploring diverse auction models and incorporating digital technologies that are increasingly prevalent in auction settings. Such studies could further validate and refine the proposed theoretical constructs, providing a more comprehensive understanding of how game dynamics influence auction outcomes.

Ultimately, this research enhances our understanding of auction mechanisms and contributes to a broader discourse on the intersection of psychology, economics, and strategy in competitive environments. As auctions continue to evolve, the insights provided in this study will be instrumental in designing more engaging, effective, and participant-centric auction platforms that cater to participants' diverse motivations.

# Chapter 6

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

This chapter is an updated and abridged version of the following publication:

- Li, Siqi and Mohd Nor Akmal Khalid, and Iida, Hiroyuki (2024). Rational bidding meets emotional viewing: the landscape of English auction livestreams in the age of algorithms. Asia-Pacific Journal of Information Technology and Multimedia, 13 (1). pp. 105–118. ISSN 2289–2192

## 6.1 Chapter Introduction

For a long time, auctions have been an indispensable part of the economic system, with ancient origins dating back to 500 BC in places like Babylon [10]. Among various auction formats, descending (Dutch), ascending (English), and sealed bidding (including first-price and second-price) stand out as the most prominent methods [71]. 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 [7].

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 [15].

Board games like "Power Grid" and "Modern Art" incorporate the bidding process of English auctions [106]. 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 [107]. 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 [108]. 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 not only engage in a transparent economic transaction but also in complex social interactions and psychological processes [109].

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.

## 6.2 Related Works

### 6.2.1 Auction Theory and English Auctions

Auctions involve transactions that sell goods and services like art, real estate, stocks, and telecommunications licenses [14]. Auction markets relate to economics and game theory [9], introducing concepts like market equilibrium and competition, facilitating a richer understanding of auction mechanisms and principles of resource allocation [7]. Auction theory studies auction markets, including the behavior of buyers and sellers and the market's nature. John Harsanyi's work in auction theory [24] paved the way for Paul Milgrom and Robert Wilson. 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 [14]. 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 [72]. English auctions are open ascending auctions where the auctioneer starts with a low bid and gradually increases it until no more bids are made [110]. 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.

### 6.2.2 Game Refinement (GR) Theory and Motion in Mind Framework

Game Refinement (GR) theory, introduced by Iida et al. in 2004 [28], 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 [2]. 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 [2, 33].

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 6-1), 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, the behaviors we observe, and the game data observable by external viewers. 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 6-1: Monitoring the Auction Process in a High-Tech Control Room.[1]

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,

[1]This figure was created by the author.

the perception of value, and the competitive dynamics of auction environments.

## 6.3 Game Refinement Theory and Motion in Mind

Player evaluations in games are shaped by game complexity and information uncertainty [2,28]. 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 model gauge the aspects of the game-playing and its entertainment values which relates to the information growth with time, given as Eq. (6.1). However, given that game-playing may involves uncertainty, a realistic information growth with time is reformulated as given by Eq. (6.2).

$$x'(t) = \frac{n}{t}\, x(t) \tag{6.1}$$

$$x(t) = \left(\frac{t}{T}\right)^n \tag{6.2}$$

Furthermore, by examining the second derivative of the information (Eq (6.3)), the game refinement metric is derived. It is denoted as the acceleration of the information growth. Generalizing the game progression to various game types and structure, the game mechanisms can be defined as Eq. (6.4), where the $G$ and $T$ were the number of options/decisions and game length/steps, respectively.

$$x''(t) = \frac{n\,(n-1)}{T^n}\, t^{n-2} = \frac{n\,(n-1)}{T^2} = a \tag{6.3}$$

$$x(t) = v = \frac{G}{T} = \frac{1}{2}\frac{B}{D} \tag{6.4}$$

Considering similar metric, in the context of the reward frequency ($N$), then additional measure can be defined as Eq. (6.5) and the third derivatives were defined as Eq. (6.6). Then, $GR$ and $AD$, which quantify entertainment experience such as thrill and unpredictability, given by Eq. (6.7) and Eq. (6.8), respectively, in games.

Table 6.1 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 ($\sqrt[3]{j} = AD$) were found, which is between $GR \in [0.07, 0.08]$, and $AD = [0.045, 0.06]$, respectively.

$$N = \frac{1}{v} \tag{6.5}$$

$$j = \frac{6G}{T^3} = \frac{3B}{D^3} \tag{6.6}$$

$$GR = \sqrt{a} \tag{6.7}$$

$$AD = \sqrt[3]{j} \tag{6.8}$$

Table 6.1: Measures of $GR$ and $AD$ for popular board games [2] [3]

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

### 6.3.1 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 (6.9)). 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 (6.10).

$$D = S_t = N_t + 1 + 1 \tag{6.9}$$

$$B = \frac{1}{N_t} \sum_{j=1}^{N_t} |A_h| = \text{Average}(|A_h|) \tag{6.10}$$

Then, the speed of the auction game can be defined as (6.11). Subsequently, the $GR$ and $AD$ of the English auction can be derived as given by (6.12) and (6.13), respectively.

$$v = \frac{1}{2} \frac{\text{Average}(|A_h|)}{S_t} \tag{6.11}$$

$$GR = \frac{\sqrt{\text{Average}(|A_h|)}}{S_t} = \frac{\sqrt{B}}{D} \tag{6.12}$$

$$AD = \sqrt[3]{\frac{3 \times \text{Average}(|A_h|)}{{S_t}^3}} = \frac{\sqrt[3]{3 \times B}}{D^3} \tag{6.13}$$

Table 6.2: 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. |

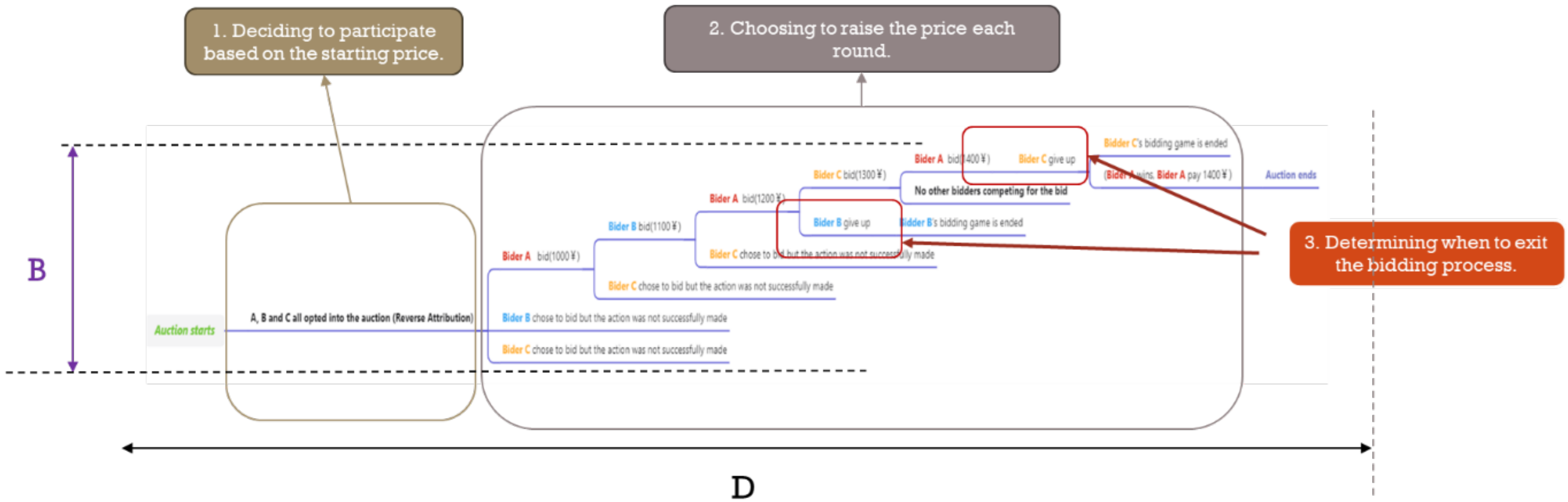



Figure 6-2: Diagram of Strategic Choices and Exit Timing in the Auction Process.[2]

### 6.3.2 Experiment Design and Data Collection

We curated a dataset of 10,000 auction items from contemporary art auctions between 2020 and 2023. The collection includes guide prices, exhibition valuations, and other relevant information for each item. To simulate a practical auction setting, we randomized the data. This dataset combines structured data, such as prices, with unstructured data, which includes bidder actions and sentiments. All data were manually collected to ensure compliance and legality. Aggregating from various digital and physical sources, we utilized multiple databases to analyze past bidding tendencies and auction outcomes. Every piece of data was meticulously preprocessed to ensure quality and coherence. After consolidating the dataset, we applied inferential statistics to identify patterns and cross-checked these findings against 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.

### 6.3.3 Simulation Scenarios

English auctions' bidding behaviors are modeled using Game Refinement (GR) Theory and the Motion-in-Mind Model, focusing on how participants collect information and estimate prices under challenges such as bias and incomplete information. Auctions, much like poker, involve participants adapting their strategies in response to their opponents' moves. This simulation not only examines participants' decision-making dynamics but also explores how their behaviors impact observers' enjoyment.

#### 6.3.3.1 Simulation Framework

The simulation framework is divided into three key components:

[2] This figure was created by the author.

- **Economic Transaction Environment:** This component establishes the foundational rules of the auction, encompassing general guidelines (e.g., English ascending auction rules) as well as seller-specific strategies. These strategies include various designs studied in Chapters 3 to 5, such as the selection of the first auction item and other seller-driven mechanisms aimed at optimizing bidder engagement. One example is the *Lure Bidding Model* (Algorithm 1), introduced in Chapter 4, which demonstrates how a strategically chosen initial item can influence bidder behavior and auction dynamics. This chapter integrates such designs into the simulation framework, drawing upon a broad range of auction house strategies and their corresponding algorithms.

- **AI Participants:** Participants are categorized into three types—*Novice Bidders*, *Bounded Rationality Bidders*, and *Rational Bidders*—each representing a different level of decision-making complexity. These categories allow for modeling a range of bidding behaviors, from simple probabilistic decisions to more complex strategies.

- **NPC System (Non-Player Characters):** The NPC system simulates auctioneers or competitive bidders, shaping participant decisions and dynamically adjusting auction parameters using historical data and real-time interactions. This system provides a structured reference for the simulation, ensuring that AI participants interact within a realistic auction environment.

#### 6.3.3.2 NPC System (Non-Player Characters)

The NPC System plays a critical role in the simulation by representing sellers or competitive bidders. It incorporates:

- **Dynamic Valuation:** Generating reference prices based on historical and guided data.

- **Participant Interactions:** Modeling how NPCs influence participants' bids through competitive behaviors.

- **Large-Scale Simulation:** Conducting 10,000 iterations across diverse auction scenarios to ensure statistical significance.

The NPC system integrates outputs from *Algorithm 5* (information gathering and valuation) and *Algorithm 6* (dynamic bidding behavior), providing a comprehensive simulation environment.

**Algorithm 5** Simulation of the information gathering and valuation process in an auction (NPC)

InputInput OutputOutput Comment/* */ Auction prices of contemporary art from 2020 to 2023 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) common_price ← calculate_common_price(guidance_price, exhibitions, history) write_to_file(participants_count, participant_estimates, common_price)

**Algorithm 6** Auction Bidding Process Simulation (NPC)

InputInput OutputOutput Comment/* */ Number of participants (num_participants), List of values (value_list), Common values (common_values) Participants' details, winner, winning price, Total bids, max/min/avg 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 Set common value, initialize winner and winning price

**for** i = 0 to 10,000 **do** {*}[r]Simulation loop

**for** each participant in participants **do**

**if** random value between 0 and 1 ¡ participant's preference **then** Update participant's bid details

Calculate final results **return** Final results

#### 6.3.3.3 AI Participant

The AI participants are categorized into three groups, each exhibiting different levels of rationality in decision making.

**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 7).

**Algorithm 7** Restricted Estimate Bidding Adjustment (Novice Bidders)

InputInput OutputOutput Comment/* */ Participant's public and private information: participant's estimate of the item's value Final bid placed by the participant $available\_assets \leftarrow$ random value between 0 and 1 {*}[r]Generate a random maximum asset value $\alpha \leftarrow$ participant's estimate of the item's value

**while** other participants continue to bid **do** $\beta \leftarrow available\_assets \times \alpha$ {*}[r]Calculate maximum bid based on random maximum asset value

**if** other participants have bid **then** $\alpha \leftarrow 1.1 \times \alpha$ {*}[r]Adjust estimate upward by 10% if others are bidding

**if** $\beta$ exceeds estimated value **then** $bid \leftarrow \alpha$ {*}[r]Submit bid equal to estimated value

**else** $bid \leftarrow \beta$ {*}[r]Submit bid equal to maximum bid $available\_assets \leftarrow available\_assets - bid$ {*}[r]Update available assets based on bid **return** final bid placed by the participant

**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 8). Meanwhile, Module II recreates the auction atmosphere where various bidders vie for a singular item, with each participant coded to ensure active engagement (Algorithm 9 and Algorithm 10).

**Algorithm 8** Information Gathering and Initial Valuation (Bounded Rationality Bidders)

InputInput OutputOutput Comment/* */ Historical auction data from 2020 to 2023 bidders_valuations

/* Initialize the AI bidders' information gathering process */ bidders_valuations ← []$\{Listtostorevaluationsofeach AI bidder\}$

**for** sample ∈ random_samples(dataset, 100) **do** participants_counts ← extract_participants_counts(sample) {Number of participants in each auction sample} guidance_price ← extract_guidance_price(sample) {Guidance price for the auction item} exhibitions ← extract_exhibitions(sample) {Information on exhibitions of the auction item} history ← extract_history(sample) {Historical auction records}

**for** participants_count ∈ participants_counts **do** participant_valuations ← $emptylist\{Listtostoreindividualvaluations\}$

**for** bidder $j$ = 1 to participants_count **do** base_estimate ← calculate_standard_estimate(guidance_price, exhibitions, history) {Base valuation using historical and exhibition data} adjustment_factor ← generate_bounded_adjustment() {Generate bounded adjustment based on probabilistic decision rules} bidder_valuation ← apply_bounded_rationality(base_estimate, adjustment_factor) {Compute final valuation under bounded rationality constraints} participant_valuations.append(bidder_valuation) {Store bidder's valuation}

common_price ← calculate_common_price(guidance_price, exhibitions, history) {Determine average/common price} bidders_valuations.append((participants_count, participant_valuations, common_price)) {Store result for this sample}

write_to_file(bidders_valuations) {Output gathered data to a file for further analysis}

**Algorithm 9** Bounded Rationality Bidders Strategy

InputInput OutputOutput Comment/* */ Auction item *item*, List of participants *participants*, Initial estimate *initial_valuation*, Budget *budget* Final bid $final\_bid$ $current\_valuation \leftarrow initial\_valuation$ $adjustment\_count \leftarrow 0$ $final\_bid \leftarrow 0$ {*}[r]Evaluate participants and set initial strategy

**for** each $participant \in participants$ **do** $participant\_evaluation[participant] \leftarrow evaluate\_participant(participant)$

**while** auction_active **do** {*}[r]Observe auction dynamics and update decisions

**for** each $participant \in participants$ **do**

**if** *participant* bids **then**

**if** $participant\_evaluation[participant] > threshold$ **then** {*}[r]Adjust valuation probabilistically based on trusted participant's behavior

**if** $random() < probability\_threshold$ **then** $delta \leftarrow \delta/(1 + adjustment\_count)$ $current\_valuation \leftarrow current\_valuation + \delta$ $adjustment\_count \leftarrow adjustment\_count + 1$

**if** $adjustment\_count \geq 3$ **then** {*}[r]Limit to 3 adjustments break

{*}[r]Submit bid if within budget and valuation $next\_bid \leftarrow generate\_bid(current\_valuation)$

**if** $next\_bid \leq budget$ **then** $final\_bid \leftarrow next\_bid$ $budget \leftarrow budget - adjustment\_count \times cost\_per\_adjustment$ submit_bid($final\_bid$)

**else** {*}[r]Exit if budget exceeded break

{*}[r]Check if auction is over $auction\_active \leftarrow check\_auction\_status()$

**return** $final\_bid$

**Algorithm 10** Bidder Belief Failure Simulation

InputInput OutputOutput Comment/* */ Number of participants $n$, Starting bid price $b_0$, Guide price $g$, Historical information $H$, Exhibit information $E$ Winning participant $p$, Winning bid price $b_p$ Initialize participants using $H$, $E$, and $g$ Set current bid price $b \leftarrow b_0$, auction end flag $end \leftarrow$ False

**while** $\neg end$ **do**

**for** each participant $i$ **do** Adjust and submit bids Determine the winner and update values **return** $p$, $b_p$

**Rational Bidders:**

Their bidding behavior strictly adheres to 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 [111] (Algorithm 11). They firmly believe in their strategies, unaffected by peer dynamics. For an immersive simulation, judgment and credit assessment modules in the highest level were incorporated.

**Algorithm 11** Process of Monte Carlo Tree Search and Bayesian Nash Equilibrium Algorithms

InputInput OutputOutput Comment/* */ Number of iterations $N$, number of rounds $R$, initial auction parameters, pre-trained model 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 **return** Optimal strategy

#### 6.3.3.4 Ensuring Realism through Algorithm Threshold Calibration

To ensure the realism of the simulation, thresholds in the NPC system and AI participants' algorithms were calibrated based on both real-world data and theoretical foundations. These thresholds define parameters such as bid increments, valuation adjustments, and decision-making intervals, ensuring realistic auction dynamics.

**Auction Theory Guidance**

Both the AI participants and the NPC system estimate the value of auction items based on conclusions drawn from auction theory. These estimations utilize either the *Benchmark Model* or the *Private Value Model*. The models are built on the following critical assumptions:

1. Single-item auctions.
2. All bidders and sellers are risk-neutral.
3. All bidders are symmetric, with valuations following the same probability distribution.
4. Auction items have independent private values, meaning a bidder's valuation does not change even with knowledge of others' valuations.
5. Final payments depend solely on the submitted bids.
6. Bidders engage in non-cooperative games.
7. The seller acts as the auctioneer, with no transaction costs.

The NPC system adopts the *Benchmark Model* to maintain a stable and structured auction environment. Meanwhile, the AI participants dynamically adjust their parameters based on varying levels of rationality and information-gathering capabilities, allowing for diverse and adaptive behavior patterns during simulations.

**NPC System Thresholds**

The NPC system operates as a static benchmark model, providing a stable and structured environment for the simulation. Thresholds were derived from:

- **Empirical Data Calibration:** Historical auction data from Sotheby's and Christie's (2020–2023) informed parameters such as guidance price ranges and bidding increments. For example, the minimum bid increment was set based on actual distributions, ensuring that NPC behaviors align with observed real-world patterns.

**AI Participants' Thresholds**

In contrast to the NPC system, AI participants' thresholds were designed to simulate varying levels of rationality and adaptability. Key features include:

1. **Dynamic Adjustments:** AI participants dynamically adjust their decision-making thresholds based on peer bidding behaviors and price trajectories. For instance, bounded rationality bidders use thresholds influenced by competitor actions, enabling adaptive decision-making.

2. **Behavioral Diversity:** Novice, bounded rationality, and rational bidders each have unique thresholds reflecting their decision-making complexity, ranging from random bidding adjustments to Bayesian Nash equilibrium strategies.

## 6.4 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, their impact of strategic deception, and their influence on the entertainment value perceived by the audience, with the aid of our simulation data (Table 6.3). 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.

Table 6.3: 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 result also indicates that $GR$ tends to lie within the comfortable zone ($GR \in [0.07, 0.08]$). With a $GR = 0.1287$, novice bidders are significantly above the comfort zone, suggesting that English auctions may feel slightly fast-paced for beginners. In contrast, rational bidders who adopt the Bayesian Nash equilibrium strategy obtained $GR = 0.0686$, slightly below the comfortable zone. This condition hinted that English auctions might seem simplistic or even uninteresting to them. For participants exhibiting bounded rationality, the $GR \approx 0.106$. 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.

The study found that the relationship between game complexity ($GR$) and fluctuation ($AD$) plays a significant role in determining player engagement and potential addiction [3]. The game becomes engaging when $GR = AD$, and players may become addicted. The researchers also discovered that the game's peak addiction occurs when reward frequency ($N$) and baseline ($B$) are set to 9 and $D$ (delay discounting) 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.

Table 6.4: Optimal Number of Participants for Different Bidder Levels under Specific Conditions

| $GR = AD$, $B = 9$, $D \in [37.5, 42.85]$ | |
|---|---|
| **Bidder Level** | **Number of Participants** |
| Novice Bidders | 18 to 20 |
| Bounded Rationality | 27 to 32 |
| Rational Bidders | $\approx 57.23$ |

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.

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 is 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) [112] noted that public pricing is typical for standard goods. 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 not only by the desire to win but also by 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.

## 6.5 Chapter Conclusions

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:

- 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.

- It became evident through the lens of GR theory that bid frequencies and magnitudes, and their relation to suspense, significantly influence entertainment value.

- 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.

- 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 study revealed the psychological and strategic factors underlying bidder behavior in English auctions. 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.

# Chapter 7

# Conclusion

## 7.1 General Conclusion

This dissertation provides an interdisciplinary framework for analyzing auction behaviors through the integration of behavioral economics, game theory, and artificial intelligence. Using Game Refinement Theory (GR Theory) and the Motion in Mind framework, this study quantitatively investigates both rational and irrational decision-making within dynamic auction environments. The conclusions emphasize dual perspective modeling, data-driven insights, and technical innovations, all of which contribute to enhancing auction system design and participant engagement.

### 7.1.1 Key Technical and Data-Driven Findings

- **Dual Perspective Model for Auction Analysis:** The dual perspective model, encompassing both internal (participant) and external (observer) viewpoints, systematically captures irrational behaviors driven by non-economic motives, such as social status signaling and entertainment value. This dual-loop utility feedback provides a comprehensive framework for analyzing complex bidder behaviors within interactive auction settings.

- **AI and Algorithmic Applications in Auction Environments:** By modeling various levels of rationality among bidders—novice, bounded rationality, and fully rational—this study leverages AI-driven simulations to reveal how each level influences auction dynamics. Utilizing GR Theory and the Motion in Mind framework, the AI models offer strategic insights for optimizing auction designs by balancing excitement with engagement. This integration of AI and economic theory enhances predictive modeling in virtual marketplaces.

- **Data-Driven Insights into Auction Dynamics and Engagement:**
  - **Average Game Velocity:** The study demonstrates that the average game velocity across auction stages is approximately 0.7, aligning with the "anticipation zone" defined in previous studies by Professors Iida and Akmal. This (v, m) data correlates closely with public gambling data, indicating similar excitement and anticipation levels in auctions, highlighting the gaming-like appeal of auctions for participants.
  - **Velocity and Price Deviation Relationship:** A significant negative correlation exists between auction velocity (bid frequency) and price deviation (difference between estimated and final prices), When the final price equals the upper limit of the estimated price and the Price Deviation Value approaches 0, participants' private information aligns with market information, a state termed 'information alignment,' akin to a game of complete information. At this point, auction velocity stabilizes around 0.54, peak market efficiency. However, this correlation diminishes as prices increase, indicating that higher prices lead to more rational participant behavior. These empirical findings, validated through real auction data, inform pricing strategies to maximize bidder interest.
  - **Impact of the First Auction Item:** The first auction item holds strategic importance, featuring a low starting price and a high "mass" value (m $\approx$ 0.72), which captures initial bidder attention and serves as a psychological anchor for subsequent bids. This selection utilizes both economic and non-economic incentives to foster deeper engagement.

  - **Core Items as Gravitational Anchors:** Core items with high value act as "gravitational anchors." The core items have a lower "mass" value, aligning with public gambling metrics, while their high prices focus attention and strengthen social identity motives such as conspicuous consumption. However, the attraction to core items can detract attention from surrounding auction items. The strategic layout of these core items enhances engagement throughout the auction, as demonstrated by data from major auction houses.

- **Lure Bidding Model for Enhanced Auction Dynamics:** Based on data from the first auction item, the Lure Bidding Model leverages low starting prices and high "mass" values to induce participants to overestimate their own skills. Additionally, this model, influenced by the "serial position effect," affects participant decision-making throughout the auction. The Lure Model provides a computational tool to optimize bidder engagement and allows AI bidders to adjust their self-evaluation, simulating both irrational and partially rational behaviors. This model assists in predicting participant strategies, making it applicable to auction design and virtual markets by linking social identity, conspicuous consumption, and psychological incentives.

- **Quantitative Metrics for Engagement and Game Utility:** Utilizing GR Theory and the external perspective model, this research quantifies audience engagement with metrics such as game velocity (v), game quality (m), and Jerk (AD). Simulations identify the optimal participant counts for various rationality levels to achieve a GR value within the ideal range of 0.07-0.08, balancing excitement and strategic depth. When game length is fixed, higher rationality levels require more opponents for audiences to maintain engagement, highlighting how the rationality of the game influences viewer preferences.

- **Practical Applications and Technological Innovations:**

  - **User Experience Optimization on Auction Platforms:** Practical recommendations include optimizing bidding speeds, item displays, and information flow to increase user engagement. These insights support the integration of virtual and augmented reality to further enhance auction interactivity and personalization.

– **Broader Applications in ICT and Social Commerce:** Insights from the external perspective model extend to livestreaming and competitive gaming, where balancing entertainment with strategy is crucial. Future research may focus on integrating these models into ICT systems to increase scalability, responsiveness, and user satisfaction in digital and live auction contexts.

## 7.2 Addressing the Research Questions

**Research Question 1:** What factors contribute to the game appeal of auctions, and can traditional game research methods such as Game Refinement Theory and Motion in Mind Theory be used to assess auctions as an economic game activity? How can Game Refinement Theory and Motion in Mind Theory be applied to evaluate this appeal?

This study demonstrates that auctions can be optimized as game-like environments by harmonizing economic and non-economic utilities. Through Game Refinement Theory and the Motion in Mind framework, the research identifies and quantifies elements—such as an average velocity measure around 0.67, when information aligns, the velocity stabilizes around 0.54—that create an engaging, game-like dynamic. This balance reveals how participants' economic motivations intersect with emotional appeal, showcasing the potential of these frameworks to assess and optimize auctions as economic games. The findings support the assertion that auctions serve as robust models for examining the game-like appeal of real-world economic interactions.

**Research Question 2:** What strategies do auction houses use to enhance auction appeal? How do special items and changes in dynamics, like auction velocity and mass, enhance participant experience and promote status signaling or conspicuous consumption?

The study finds that strategic selection and timing of auction items play a pivotal role in maximizing bidder engagement. Specifically:

- **First Item as a Lure:** Setting a lower initial price with a higher "m" value encourages early engagement by lowering entry barriers, accelerating interest through "velocity" adjustments.

- **Core Item as a Gravitational Anchor:** Assigning higher "mass" to core items focuses attention and reinforces social identity drivers, particularly conspicuous consumption.

- **Attention Shift Simulation:** This model captures optimal engagement flow within auctions by strategically positioning items.

These strategies inform a computational framework for engagement flow optimization, providing actionable insights for enhancing user experience in digital auction platforms and e-commerce systems.

**Research Question 3:** What impact do live-streamed auctions have on audience engagement? How do the boundaries between entertainment value and rational decision-making influence participants' behavior, and how can these elements be optimized to enhance the auction experience?

This research establishes that live auctions attract audiences by blending entertainment and strategic elements, increasing engagement through non-economic utility. Key components of the external perspective model illustrate how entertainment and strategy are balanced to maximize engagement:

- **Non-Economic Utility in Audience Engagement:** Leveraging mirror neuron and social recognition theories, this model shows that audiences derive social value from observing auctions, enhancing engagement through a feedback loop.

- **Audience Interest Measurement:** The external model quantifies engagement through Game Length (D) and Average Observed Outcomes (B), showing how auction dynamics hold audience attention.

- **AI Simulations:** Varying AI bidder types (Novice, Bounded Rationality, Rational) within simulations reveal how different bidder rationality levels affect the auction atmosphere, offering actionable insights into balancing entertainment and strategy in virtual environments.

**Research Question 4:** What motivates participants to engage when facing initial uncertainty, and how do economic and non-economic utilities together influence decision-making in these contexts? Additionally, how can insights from economic structures contribute to the improvement of AI algorithms?

This study demonstrates that participants are driven by a combination of financial incentives (economic utility) and social factors (non-economic utility), creating a dynamic, game-like auction environment.

- **Economic and Non-Economic Utility:** Auctions attract participants seeking both tangible rewards and social recognition, enhancing the game-like appeal.

- **Internal and External Perspective Models:** These models reveal how participants respond to design features and psychological cues, engaging participants through an evolving feedback loop.

- **AI Simulation of Decision-Making:** Simulations with varied bidder rationality reveal how rational and bounded rationality strategies influence bidding patterns, offering a foundation for refining AI to better emulate human behavior under uncertain conditions.

The integration of economic structures with game utility insights enhances AI's predictive capabilities, paving the way for innovative applications in virtual marketplaces, recommendation engines, and real-time auction simulations.

## 7.3 Theoretical Significance and Practical Application Value

This research makes significant contributions to both theory and practice, providing a new perspective on auction behavior and laying the foundation for understanding complex economic actions and their underlying irrational motivations:

- **Theoretical Contributions**: This study proposes a novel framework for analyzing auction behavior, introducing the concepts of "game utility" and "non-economic utility" through the application of the Game Refinement Theory and Motion in Mind framework. This framework reveals the complex motivations behind auction participation, moving beyond the rational decision-making assumptions in traditional economic models. It offers new methodologies for future economic game modeling and extends the applications of behavioral economics within computer science.

- **Practical Applications**: The findings of this study provide concrete optimization strategies for online and live auction platforms. By adjusting bidding speed, designing item displays, and refining information dissemination, auction platforms can enhance user experience, increasing both viewer and bidder engagement. The AI behavioral prediction model can also assist auction platforms in digital economies by attracting users and optimizing item recommendation strategies to meet diverse user needs.

- **Cross-Disciplinary Potential**: The proposed behavior modeling approach introduces a novel interdisciplinary method for understanding and optimizing complex human behavior. Beyond auctions, these insights offer applications in broader economic and social contexts, particularly in areas requiring an understanding of both rational and non-rational incentives. This interdisciplinary framework has the potential to contribute to behavioral economics, computer science, and social psychology by providing a deeper understanding of market dynamics and user motivations.

## 7.4 Study Limitations and Suggestions for Future Research

While this study achieves significant progress in modeling auction behavior, several limitations remain, suggesting avenues for future research:

- **Data Limitations**: The study's data primarily comprises modern art auctions from specific regions. Future research could extend the data set to include diverse categories (e.g., real estate, luxury goods) and geographic regions, particularly examining the model's applicability in culturally distinct markets. This would improve the model's robustness and generalizability.

- **Experimental Verification**: Some model validations rely on theoretical derivation and AI simulations, with limited experimental testing. Future studies could involve real auction experiments to observe behavior under specific conditions, thereby enhancing the model's applicability in real-world settings and further analyzing the role of non-economic motivations across varied auction scenarios.

- **Computational Complexity**: Due to the high dimensionality of the model, the research depends on high-performance computing systems (e.g., the "KAGAYAKI" system for JAIST) for simulation. Future research could focus on algorithm optimization, simplifying the model structure to maintain efficiency in resource-limited environments, and support broader application scenarios.

## 7.5 Future Research Directions

Based on the limitations identified, future research can focus on the following areas:

- **Expanding Data Coverage and Applicability**: This framework could be applied to other auction types and broader geographic areas to assess its generalizability. Examining behavior patterns in auctions across diverse social and cultural contexts could further validate the model.

- **Enhancing Experimental Design and Behavioral Observation**: Future studies could incorporate experimental designs with human participants to directly observe behavior across various auction scenarios, validating the roles of conspicuous consumption, audience interaction, and emotional drivers in diverse settings.
- **Expanding Data Coverage and Applicability**: This framework could be applied to other auction types and broader geographic areas to assess its generalizability. Examining behavior patterns in auctions across diverse social and cultural contexts, such as comparing Western and Asian market tendencies, could validate the model's robustness and reveal cultural influences on non-economic motivations, such as social status signaling and entertainment value.
- **Optimizing Algorithms and Introducing Multi-Agent Systems**: Combining Reinforcement Learning (RL) and Multi-Agent Systems (MAS) could enable more efficient auction behavior prediction models that meet real-time data processing demands. Additionally, integrating cognitive experiments may further validate the AI model, allowing for more accurate user behavior prediction and supporting future economic activity simulations.

## 7.6 Closing Remarks and Prospects

Auctions are not merely economic transactions but also complex social interactions, especially in live environments where they serve as platforms for self-presentation, identity expression, and competition. Modern auctions, particularly live-streamed ones, blend economic utility with social utility, reflecting not only participants' rational strategies but also their social identities and conspicuous motivations. As globalization and digitalization progress, the forms and meanings of auctions continue to evolve, positioning auctions as an intersection of economic activity and social culture and providing a rich field for studying complex economic behaviors.

The conclusions of this study suggest that "game utility" and "non-economic utility" in auctions not only shape bidders' strategies but also embody complex social motivations, including social interactions and identity expression. The AI-driven models developed in this research employ multi-agent systems (MAS) and reinforcement learning (RL) techniques to simulate participant behavior within dynamic auction environments. MAS enables a competitive, game-like interaction among AI agents, capturing both rational and bounded-rational behavior patterns, while RL further enhances the system by allowing agents to learn adaptive bidding strategies through real-time feedback from auction dynamics. This combination not only strengthens the model's predictive accuracy but also demonstrates the adaptability of AI in replicating complex economic systems.

Given the rapid advancements in AI and computational intelligence, future studies could further explore computational complexity optimizations, such as dimensionality reduction techniques and resource-efficient algorithms, to enable real-time simulations on less resource-intensive systems. While the computational models in this research rely on high-performance computing (e.g., the KAGAYAKI system), algorithmic simplifications could broaden their applicability to more accessible platforms, including mobile and web-based auction environments.

This interdisciplinary framework also presents promising applications in AI-driven recommendation systems. By capturing users' social motivations and economic preferences, the model can enhance item recommendations, refine audience targeting, and personalize user experiences in digital marketplaces and e-commerce platforms. As auctions increasingly shift to digital and "phygital" (physical-digital hybrid) formats, future research could explore augmented reality (AR) integration to create immersive auction experiences and extend economic interaction to new contexts. This expansion of auction simulations opens new avenues for applying behavioral economics insights within AI applications, contributing to a nuanced understanding of user engagement, decision-making patterns, and preference modeling in virtual marketplaces.

By integrating interdisciplinary perspectives, this research offers new directions at the intersection of behavioral economics, computer science, and social psychology, enriching our understanding of modern auction dynamics within both economic and social contexts.

In summary, this dissertation establishes a robust interdisciplinary framework for analyzing auction dynamics by integrating behavioral economics, AI, and game theory. Through this framework, the research highlights the significant role of non-economic utilities, such as game utility and social motivations, in participant engagement. The AI-driven models and dual-perspective analysis developed in this research have potential applications in various economic and digital environments, from virtual auctions to social commerce. Future studies can build upon this foundation, further refining AI models and exploring auction behaviors in culturally diverse and digital-first settings.

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[1] Li, Siqi; Mohd Nor Akmal Khalid; Hiroyuki Iida. (2024). Rational Bidding Meets Emotional Viewing. Asia-Pacific Journal of Information Technology and Multimedia, Vol.13 (1), 105–118.

[2] Li, Siqi; Mohd Nor Akmal Khalid; Hiroyuki Iida. (2024). Strategic Selection and Design of the First Auction Item: Analyzing Auction Dynamics through "Motion in Mind" and "Potential Reinforcement Energy". Asia-Pacific Journal of Information Technology and Multimedia, Vol.13 (2), 298–312.

[3] Pan, Yizhi; Xin, Junyi; Yang, Tianhua; Li, Siqi; Nguyen, Le-Minh; Racharak, Teeradaj; Sun, Guanqun. (2024). A Mutual Inclusion Mechanism for Precise Boundary Segmentation in Medical Images. Submitted to Frontiers in Bioengineering and Biotechnology, section Biosensors and Biomolecular Electronics.Vol 12 - 2024

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[4] Li, Siqi; Mohd Nor Akmal Khalid; Hiroyuki Iida. (2023). Rational Bidding Meets Emotional Viewing: The Landscape of English Auction Livestreams in the Age of Algorithms. The 12th ASEAN Workshop on Information Science and Technology (AWIST 2023).

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# Appendices

The interdisciplinary nature of this dissertation, which lies at the intersection of computer science, economics, and game theory, necessitates the inclusion of supplementary material to provide a broader context for the computational models and methodologies discussed. While the primary focus of the dissertation is on the technical contributions within the realm of artificial intelligence and auction systems, it is essential to acknowledge that these topics are deeply rooted in established economic and game-theoretic principles.

In order to maintain the clarity and focus of the main chapters on the technical innovations and analyses, I have relegated certain foundational discussions—such as the historical evolution of auctions, the theoretical underpinnings of utility theory in economics, and the distinctions between economic and non-economic games in game theory—to the appendix. This approach allows the dissertation to remain concise and focused on its core research objectives, while still providing readers with the necessary background material to fully understand the interdisciplinary connections that inform this work.

By situating these discussions in the appendix, I ensure that the primary content remains tightly aligned with the objectives of a computer science thesis, while offering a comprehensive reference for readers who may wish to explore the broader theoretical context of the research.

# Appendix A

# Economic Literature Review

## A.1 Introduction

Firstly, this paragraph provides a comprehensive review of the literature on economics, focusing on conspicuous consumption, utility theory, and behavioral economics. The objective is to explore how non-economic incentives and game-like behaviors influence economic decision-making, especially in contexts where rationality is not the only driving force. These frameworks are particularly useful for understanding non-monetary incentives that drive decision-making, beyond traditional economic models.This helps to explore how decision-making under uncertainty is motivated by both economic and social rewards, such as social recognition, status, and identity.

## A.2 Classical Economics

Classical economics, founded by Adam Smith and David Ricardo, emphasizes the self-regulating mechanisms of markets, primarily through supply and demand forces, under conditions of minimal governmental intervention [45]. A key component of this framework is the labor theory of value, which posits that the value of a good is derived from the labor required for its production [113]. These foundational principles have significantly influenced contemporary economic theory, particularly in analyzing market dynamics and transactions.

In classical economics, markets are assumed to operate efficiently with rational agents who aim to maximize their utility [46]. This assumption is particularly relevant in transactional markets, where competitive interactions are expected to facilitate transparency and the efficient allocation of resources. Transactions, in this context, function as mechanisms that allocate goods or services to participants who value them most, with prices determined by the interaction of supply and demand [22].

However, the classical economic model assumes conditions of perfect competition and fully rational actors—assumptions that are often not reflected in real-world transaction environments. Challenges such as information asymmetry, psychological factors, and externalities can lead to deviations from the idealized market models proposed by classical economists [47]. While classical economics emphasizes rational decision-making, it often fails to account for these complexities. In response, newer economic models, such as those in behavioral economics, address these gaps by incorporating insights into how psychological and social factors influence decision-making in market transactions [35].

## A.3 Behavioral Economics

Behavioral economics challenges the traditional economic assumption of rationality, which posits that individuals consistently make decisions to maximize their utility. Originating from the work of psychologists Daniel Kahneman and Amos Tversky, this field demonstrates that people often deviate from rational decision-making, especially under conditions of uncertainty or risk [48]. Their Prospect Theory, a cornerstone of behavioral economics, explains how individuals perceive gains and losses asymmetrically, often placing more weight on avoiding losses than on achieving equivalent gains—a concept known as loss aversion.

In addition to loss aversion, behavioral economics explores various cognitive biases that influence decision-making. For example, people may exhibit overconfidence, overestimating their ability to predict outcomes, or they may rely heavily on anchoring, where initial information disproportionately impacts subsequent judgments [49].

These biases result in decisions that deviate from the rational utility maximization models outlined by classical economics.

Furthermore, Kahneman's dual-system model of decision-making—outlined in his book Thinking, Fast and Slow—has been instrumental in explaining how these biases operate [114]. According to this model, System 1 (intuitive and automatic) handles quick, heuristic-based judgments, while System 2 (deliberate and analytical) governs slower, more reasoned thinking. In complex or uncertain environments, System 1 often dominates, leading individuals to rely on cognitive shortcuts and, consequently, biased decisions.

Behavioral economics and cognitive psychology, therefore, provide a comprehensive framework for understanding how individuals make choices in competitive and uncertain settings, such as markets or economic games. This perspective highlights the role of social, psychological, and emotional factors in economic transactions, suggesting that market participants may base decisions on perceived risks, social influence, or cognitive limitations rather than purely on rational utility maximization [50]. By integrating insights from psychology, this framework offers a more nuanced view of decision-making, revealing how irrational tendencies shape economic interactions.

### A.3.1 Emotions and Intuition in Decision-Making: Insights from Behavioral Studies

The impact of emotions on decision-making, especially under conditions of uncertainty and risk, has been a subject of study by cognitive psychologists, including Annie Duke, who brings insights from her experience as a professional poker player. Her research emphasizes the importance of emotional regulation and intuition in effective decision-making, particularly in high-stakes situations where outcome judgments often cloud objective assessment [115]. Duke's work complements behavioral economics by highlighting that decisions are influenced not only by cognitive biases but also by emotional factors, underscoring the complexity of decision-making beyond rational calculations.

## A.4 Leisure Economics

Thorstein Veblen, in his work *The Theory of the Leisure Class: An Economic Study in the Evolution of Institutions*, introduced the concept of "conspicuous consumption." This refers to the behavior where consumers purchase goods at prices higher than their actual value [25]. For conspicuous consumers, publicly displaying disposable income serves as an economic means to attain or maintain a certain social status. This behavior is not solely for the acquisition of the goods themselves, but rather to demonstrate personal wealth and social standing through the possession and use of these goods. Such ostentatious display may aim to evoke envy in others, satisfying one's vanity; however, it can also stem from a sense of sympathy, where conspicuous consumption is used to enhance a donor's reputation and social prestige through charitable activities.

Andrew Trigg (2001) defined conspicuous consumption as the act of demonstrating substantial wealth by idleness—spending a significant amount of time in leisure activities, and expending considerable funds on luxury goods and services. Conspicuous sympathy, the practice of publicly donating large sums to charity organizations to enhance the donor's social prestige, is sometimes described as a form of conspicuous consumption [26]. Indeed, as noted by Wang Yongbin, a Qing Dynasty writer in his *Fireside Chats*, "A gentleman judges deeds, not intentions" [116] [117]. Thus, using charity conspicuously to improve a donor's reputation and social standing can have a positive impact on society.

# Appendix B

# The History and Evolution of Auctions

## B.1 Introduction

Auctions have a long and complex history, characterized by the development of clear transaction rules and bounded transaction times. These rules have evolved over centuries to reflect not only the economic needs of societies but also the behavioral patterns of human participants in economic exchanges. The consistency of auction rules across different cultures and historical periods reveals that auctions are one of the most effective mechanisms for resource allocation.

However, auctions are more than just economic mechanisms—they represent structured, rule-based environments where competition, strategy, and, increasingly, non-economic factors such as social prestige and psychological engagement play significant roles. Understanding the historical evolution of auctions provides insight into how auction systems today function, not just as market tools, but as complex social interactions influenced by a variety of motivations.

This historical context is essential for analyzing modern auction practices and the economic, psychological, and social factors driving participant behavior. The exploration of auction history lays the foundation for linking these insights to classical economic theories, game theory, and behavioral economics, as well as to the emerging field of "game utility" in auctions.

## B.2 The Origins and Early Forms of Ancient Auctions

The origins of auctions can be traced back to ancient civilizations such as Babylon and Rome, where they served primarily as mechanisms for the sale of goods, land, and even people. One of the earliest documented auctions took place in Babylon, as described by Herodotus in Histories [10]. In Babylonian society, auctions were used to arrange marriages, with brides auctioned off to the highest bidder. These early forms of auctions primarily served economic functions, facilitating the exchange of goods and services in a competitive environment.

Similarly, auctions flourished the Roman Republic era(510 - 27 BC), where they became a key tool for selling war spoils, estates, and slaves. The Roman auction system, known as "atrium auctionarium," introduced structured bidding sequences, where auctioneers set the terms, and participants competed based on their bids [22]. The development of rules such as ascending price auctions reflected the growing sophistication of the Roman economy and the need for efficient and competitive resource allocation.

These early developments laid the groundwork for the formalization of auction rules and competitive bidding, concepts that would later become integral to auction theory. They also reflect how auctions began to serve not only as market tools but as competitive social spaces, where the act of bidding itself was governed by rules designed to balance fairness, competition, and economic efficiency.

## B.3 Auctions in Asia

Parallel to developments in Europe, auctions in Asia—particularly in ancient China—evolved within specific cultural and religious contexts [69] [70]. From the 5th century, pawnshops began to appear in temples, leading to the development of an auction system that became prominent by the 7th century [23]. During the Tang and Song dynasties, temple auctions became especially significant, primarily handling the personal belongings of deceased monks, including clothing and other personal effects. The auction process often began with the recitation of scriptures for the deceased, after which the auctioneer monk would present the condition and suggested price of the items. The proceeds from these auctions, after deducting funeral expenses, were distributed among the monks who participated in the chanting, funeral services, or the auction itself [23].

In ancient China, auction mechanisms were adapted to serve various societal needs beyond mere economic transactions. Auctions became a way to redistribute wealth within the community and support religious institutions, making them a vital part of both the economic and social structure. Notably, the dominant auction format in ancient China was the ascending-price auction, where bids would increase progressively until the highest bid secured the item. This form of auction, similar to the modern English auction, was commonly used in temple auctions and other communal sales, reflecting the competitive yet structured nature of the bidding process [69]. The prevalence of auctions highlights the flexibility and adaptability of auction practices, which were shaped by the cultural norms and societal needs of the time. These auctions were not only a means of fundraising but also played a significant role in providing economic and social support within the temple community. By integrating religious ceremonies into the auction process, these events became more than simple transactions—they reflected the deep integration of economic, social, and cultural life.

## B.4 From the Middle Ages to the Early Modern Period: The Evolution of Auction History

During the Middle Ages, auctions began to take on more formalized structures, particularly in Europe. Auctions were not only a part of economic transactions but also became embedded in social life, where they served as public events, attracting bidders and onlookers alike. Auctions often took place in town centers, becoming a source of entertainment, gossip, and social bonding. The rise of auction houses such as Sotheby's in 1744 and Christie's in 1766 marked the institutionalization of auctions, where rules and standards were established to regulate transactions. These auction houses were initially established to cater to the growing demand for art and luxury goods, reflecting the evolving tastes of the emerging merchant class. This institutionalization reflected the growing complexity of market economies and the need for formal mechanisms to ensure fairness, transparency, and competition.

This period also saw a significant shift in the types of goods being auctioned. While auctions had traditionally focused on land, property, and other essential goods, the Renaissance brought a rise in the sale of art, rare collectibles, and exotic items. Prominent families, such as the Medici in Italy, played a key role in fostering the development of art auctions. Works by renowned artists such as Leonardo Da Vinci and Michelangelo were sold at these auctions, attracting wealthy patrons and cementing the importance of auctions as a way to acquire cultural and artistic goods [118]. The development of specialized auction houses during this time marked a shift from informal, local auction environments to more organized and structured settings [119].

In the United States, auctions also developed, with early records predominantly centered in the South, where auctions were used to sell slaves, alongside estate liquidations. The anonymity of auction item owners was often a societal norm, especially during these early years of American auctions [120]. Outside of Britain and the United States, auction mechanisms were also being adopted in other regions, such as the Netherlands and Germany. The Dutch auction system, which dates back to 1887, became popular for the sale of perishable goods like fruits and vegetables, while German fishermen began using auctions to sell their catch upon arrival at ports [29]. These developments highlight how auctions became essential tools for various types of transactions across different industries.

In the mid-19th century, Paris re-emerged as a prominent auction center, driven in part by the wealth of collectors such as James de Rothschild and Richard Seymour-

Conway [63]. The founding of the state-sponsored Hôtel Drouot auction house in the 1850s further cemented Paris's role in the global auction industry [121]. Similarly, Britain saw a surge in auctions of aristocratic collections following the agricultural depression of the 1870s and the introduction of death duties in 1894 [122]. This trend continued into the 20th century, with British auction houses experiencing great prosperity until the stock market crash of 1929. Meanwhile, in the United States, the first art auction house, the American Art Association, was established in 1883, though the art auction business developed slowly there [123].

By the early 20th century, the influence of American collectors and art dealers became a significant force in the global art market. Figures such as Andrew W. Mellon and Henry Clay Frick played a pivotal role in assembling some of the greatest private collections in American history [124]. By the mid-20th century, New York had overtaken Paris as the center for modern and contemporary art, driven by key players such as Peggy Guggenheim and art dealers like Leo Castelli [125]. New York auctions were instrumental in promoting the works of contemporary artists, particularly after the landmark 1973 auction of Robert Scull's Pop art collection. This shift marked a broader change in the global auction market, with auction houses expanding their operations into new regions, including East Asia, Australia, and continental Europe [126]. Innovations such as telephone bidding and satellite links were introduced, turning auctions into glamorous, celebrity-filled events.

An important aspect of the auction market in the 20th century was the diversification of goods being sold. Auctions expanded beyond traditional art and antiques to include categories such as classic cars, fine wines, luxury jewelry, and even pop culture memorabilia. This period saw growing interest in items like Victorian-era paintings, vintage cars, and rare coins, reflecting a broader range of tastes and collecting trends. Specialized auctions also emerged to cater to these markets, with auction houses responding to changing consumer preferences by offering more tailored sales events and developing new auction methodologies to accommodate various industries.

The Dutch flower auctions and Japanese fish auctions serve as prime examples of how auction systems adapted to specific market needs. The Dutch auction system, used primarily for selling perishable goods like flowers, operates with prices starting high and decreasing until a bidder accepts the current price. In contrast, Japan's fish auctions, exemplified by the Tsukiji market, are known for their speed and efficiency, essential for trading perishable items like seafood. These innovations demonstrate how auction formats have evolved to meet the unique demands of different industries while maintaining the core principles of competitive bidding and time-bounded transactions.

Overall, the 20th century was a period of dynamic change for the auction market, shaped by global economic shifts, technological advancements, and evolving consumer interests. This diversification in the types of goods sold and the introduction of new auction formats reflected broader cultural and economic trends, positioning auctions not just as platforms for commercial exchange but as reflections of societal change.

## B.5 Bridging Auction History with Modern Economic Theories

The evolution of auctions from ancient times to the modern era provides a crucial backdrop for understanding how economic behavior in auctions is analyzed today. Classical economic theories, particularly those related to supply and demand, market equilibrium, and resource allocation, offer a foundational perspective on how auctions facilitate price discovery and the efficient distribution of goods.

However, the increasing complexity of auctions, particularly with the involvement of high-value goods such as art and real estate, highlighted the need for a more nuanced understanding of participant behavior. Traditional economic models, focused primarily on rational decision-making, were limited in their ability to explain why participants might overbid, underbid, or engage in seemingly irrational behaviors during auctions.

The introduction of game theory by Vickrey [7] transformed the analysis of auctions by modeling them as structured competitive environments. Game theory focuses on how participants strategize based on the actions of others, often in situations of uncertainty. This strategic approach provides insights into how participants navigate auctions to achieve the best possible outcomes, taking into account both their own preferences and the actions of their competitors.

# Appendix C

# A Review of Auction Theory

## C.1 Introduction

Auction theory is a branch of economics and a subfield of game theory that analyzes bidding strategies and auction designs. Researchers use game theory to study the dynamic equilibria in auctions, dealing with the unobservable values of each buyer to understand how auction participants behave in the market and how the characteristics of the auction mechanism affect the outcomes. The goal is often to find the optimal bidding strategies that lead to desired outcomes [127].

Auctions serve as a mechanism to sell a variety of goods and services, such as art, real estate, stocks, and telecommunications licenses. In an auction market, sellers present the goods or services to potential buyers and aim to achieve the highest possible price.

Economics and game theory are closely related in the study of auction markets. From an economic perspective, theories such as market equilibrium, competition, and contract theory provide fundamental insights into the mechanisms and resource allocation principles of auction markets. Game theory offers a robust analytical framework for studying the strategic choices and interactions among participants in auctions. It is extensively applied in auction rule design, bidding strategy analysis, market competition analysis, and auction form comparison. Together, economics and game theory provide powerful tools for understanding auction markets.

## C.2 Differences Between Auctions

The differences between auction types are mainly reflected in two aspects: information and format.

Auction theory studies various aspects such as auction types, bidding strategies, market structure, competitive environment, and final results. Auction types include English auctions, Dutch auctions, first-price sealed-bid auctions, and second-price sealed-bid auctions. Different auction types influence the behavior and strategies of sellers and buyers differently.

In auction markets, the behavior of buyers and sellers is governed by the structure and nature of the market. For instance, in a single-item auction market, there is one seller and multiple potential buyers; the seller decides which buyer to sell the item to based on the bids. In a multi-item auction market with multiple sellers and buyers, participants need to consider the behaviors and strategies of others more comprehensively.

By studying auction theory, economists can understand the behaviors and strategies of different players in the auction market and provide optimal decision support to achieve desirable outcomes for sellers and buyers.

### C.2.1 Different Auction Types

To effectively analyze auctions, it is crucial to explore the variations in auction formats, each influencing participant behavior and strategy in distinct ways. Auctions can be broadly categorized into Single Auction and Multiple Auction formats, with further subcategories that shape participant interactions uniquely.

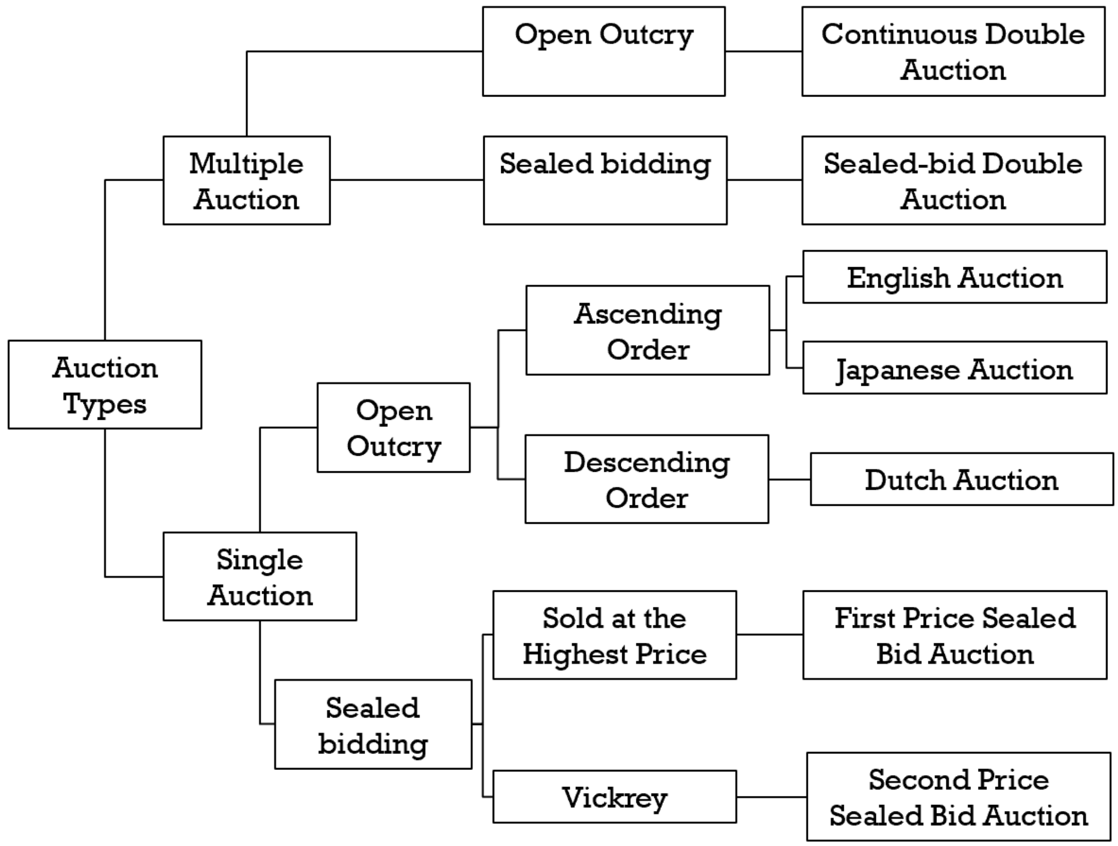


Figure C-1: Auction Types.[1]

#### C.2.1.1 Single Auctions

Single Auctions can be divided into two primary types based on the auctioneer's mechanism: Open Outcry and Sealed Bidding. Each method further diversifies into specific auction forms, characterized by ascending or descending orders.

**English Auction (Ascending Order – Open Outcry)**

The English auction is an ascending-price auction, where participants openly bid against one another, and the highest bid wins. This format encourages transparency and open competition, commonly used for luxury items like art and collectibles. The process of incremental bidding not only fosters social visibility and competition but

[1]This figure was created by the author.

also introduces a psychological phenomenon known as "auction fever," where excitement can lead to bids that surpass rational economic valuations. This non-economic utility—derived from the thrill and social interaction—makes English auctions an ideal context for studying non-economic motivations in a competitive setting.

**Dutch Auction (Descending Order – Open Outcry)**
In contrast, Dutch auctions operate on a descending price mechanism. The auctioneer starts at a high price and gradually lowers it until one bidder accepts the current price. This format is often used for perishable goods or items with high time sensitivity, such as fresh flowers or seafood. The sense of urgency and quick decision-making required in Dutch auctions heightens emotional responses like anxiety and excitement, which adds to the non-economic utility of participating in a time-sensitive bidding process. The distinct psychological dynamics make Dutch auctions another valuable model for observing how participants' behaviors are influenced by non-economic factors.

**First-Price Sealed-Bid Auction (Sealed Bidding – Single Item)**
In first-price sealed-bid auctions, participants submit bids privately, unaware of others' offers, with the highest bid winning. This format emphasizes strategic foresight, as bidders must balance the desire to win with the risk of overpaying. In terms of game theory, it involves incomplete information and strategic misrepresentation. Participants often experience suspense and strategic anticipation, and while it has non-economic utilities such as secrecy and risk management, its closed nature makes it less ideal for observing real-time participant interactions, which are central to this research's focus on non-economic motivations.

#### C.2.1.2 Multiple Auctions

Multiple Auctions encompass formats where participants bid on more than one item simultaneously, including Continuous Double Auction and Sealed-Bid Double Auction. These types are commonly used in stock exchanges or markets where multiple buyers and sellers interact, contributing to a competitive and fast-paced environment.

**Continuous Double Auction (Open Outcry – Multiple Items)** In a continuous double auction, multiple buyers and sellers place bids and asks openly and continuously, allowing for dynamic price adjustments until matching bids and asks are executed. This format is often used in stock exchanges, where rapid decision-making and real-time competition create an environment rich in non-economic motivations like urgency, excitement, and social dynamics. The complexity of interactions and the rapid pace make it a valuable model for observing real-time strategic adjustments under high levels of competition and uncertainty.

**Sealed-Bid Double Auction (Sealed Bidding – Multiple Items)** In a sealed-bid double auction, buyers and sellers submit their bids and asks in private, with transactions occurring when prices align. This format reduces transparency compared to open outcry auctions, focusing on strategy and the anticipation of other participants' offers. The privacy involved in sealed bidding adds to the non-economic utility by introducing elements of suspense and strategic secrecy. While less interactive in real-time than continuous double auctions, sealed-bid double auctions highlight strategic decision-making and risk assessment under conditions of incomplete information.

### C.2.2 Connecting Auction Characteristics to Research Objectives

The above auction types underscore the significance of studying both economic and non-economic incentives within auction environments. Auctions, with their structured and rule-based nature, align closely with game theory principles, allowing for the quantification of economic decisions. At the same time, elements of competition, uncertainty, and social interaction create a fertile ground for analyzing non-economic motivations. This combination makes auctions a valuable model for exploring broader questions of how non-economic utility influences economic decision-making.

Given the diversity of auction types, each format presents unique characteristics worthy of study. However, since this research focuses on the role of non-economic utility, it is essential to choose auction types that facilitate the observation and measurement of participants' behaviors, including those of potential bidders who may simply be observing. Therefore, this study primarily examines open outcry auctions, specifically the English auction and Dutch auction. English auctions, commonly involving luxury items and art, enable the clear distinction between economic and non-economic utilities. Dutch auctions, often used for time-sensitive goods, such as flowers, fish, bring a unique dynamic due to their rapid pace. Consequently, this research emphasizes English auctions for initial analysis, with plans to extend to Dutch auctions to explore varying impacts on non-economic motivations.

From auction theory, we understand that auctions represent a Bayesian equilibrium game and can be viewed as a zero-sum game between buyers and sellers, excluding intermediaries like auction houses or proxy bidders. Participants have access to both public information (such as auction rules and past prices) and private information unique to each bidder. The resulting information asymmetry and decision-making under uncertainty are distinguishing features of auctions. Additionally, auctions provide the option to "stop bidding," allowing a participant to withdraw without financial loss. Winning an auction at a price higher than the item's true value introduces the risk of the winner's curse, underscoring the role of non-economic motivations in decision-making. The decision models and algorithms developed through auction simulations can be adapted to analyze other economic scenarios with similar game structures, contributing valuable insights into the interplay of economic and non-economic incentives in complex environments.

## C.3 Auction Theory

Auctions are mechanisms widely used for the transaction of various goods and services, such as artwork, real estate, stocks, and telecommunications licenses. In auction markets, sellers present their goods or services to potential buyers, aiming to achieve the highest possible price. When studying auction markets, economics and game theory are often closely intertwined. From an economic perspective, these theories provide fundamental concepts for auction theory, such as market equilibrium, competition, and contracts, which help us better understand the mechanisms of auction markets and the principles of resource allocation.

Auction theory is a branch that studies the behaviors of buyers and sellers in auction markets, as well as the structure and nature of these markets. In auction theory, the roles of economics and game theory are irreplaceable; together, they offer powerful theoretical tools and analytical methods for understanding auction markets. Game theory provides a practical analytical framework for economics to study the strategic choices and interactions among participants in auctions. This theory was developed by William Spencer Vickrey and others. Researchers use game theory to analyze dynamic equilibria in auctions, dealing with the unobservable values of each buyer, to study how auction participants behave in the market and how the characteristics of the auction market function to achieve desired outcomes, aiming to find the best bidding strategies [7].

Auctions are typical examples of economic entities engaging in games of incomplete information, where information is not equally shared. Auction theory, which analyzes such interactions, was first introduced by William Vickrey in his 1961 publication *Counterspeculation, Auctions, and Competitive Sealed Tenders* [7]. Building upon John Nash's foundational work on non-cooperative games [62], Vickrey extended game theory to study auctions, addressing challenges such as buyers' unobservable values and proposing allocation mechanisms that benefit all parties.

Vickrey's work introduced the concept of the Vickrey auction, a sealed-bid auction format strategically equivalent to the English auction but designed to be incentive-compatible, motivating bidders to bid their true values [14]. This innovation laid the groundwork for modern auction designs and established the Vickrey auction as a widely used format for single-item auctions.

Auction theory also draws on earlier contributions, such as Augustin Cournot's "duopoly model" in 1838 [128] [129] and John von Neumann and Oskar Morgenstern's "Zero-Sum Game Theory" in 1944 [8]. These foundational theories, combined with

Nash's proof of the existence theorem for *non-cooperative games* [62], have significantly influenced the development of mathematical models for auction analysis.

## C.4 Development and Improvements in Auction Theory

In his 1977 book *Rational Behavior and Bargaining Equilibrium in Games and Social Situations* [24], John Harsanyi introduced an equilibrium concept that allowed Paul Milgrom and Robert Wilson to study auctions without relying on the independence assumption. This development paved the way for creating new auction theory models, making it possible to analyze more complex auction scenarios.

Milgrom and Wilson's groundbreaking research in auction theory and market design led to them jointly receiving the Nobel Prize in Economic Sciences in 2020 [14]. The impact of their work can be seen in various industries such as telecommunications, natural gas, oil, and art, significantly influencing economics, game theory, and auction theory.

They created new auction formats and strategies now used in various types of auctions, both open and private. Additionally, they solved several auction-related problems, such as determining the starting price and helping bidders determine their maximum bids. Milgrom's significant contribution to auction theory was the development of the common value auction theory [31], which assumes that the true value of the sold item is the same for all bidders, but each bidder has their own estimate of that value. They also developed the symmetric ascending auction, a new auction format for multiple items, and introduced the dynamic revenue auction, which allows bidders to learn more about the auction as it progresses and adjust their bids accordingly.

Wilson's work in auction theory is also essential. In 1969, he published a paper introducing a theoretical model for analyzing optimal auction strategies [30]. In 1982, he and Milgrom proposed a new combinatorial auction format, which has been widely used in industries such as telecommunications and energy. He also collaborated with Preston McAfee to develop the proportional auction, which ensures that bidders' bids are proportional to their values [9].

Besides their contributions to auction theory, Milgrom and Wilson have also made significant advancements in market design. For example, they proposed a new market design called the common value auction, widely used in the telecommunications, oil, and gas industries. This design is intended to encourage bidders to reveal their true values for the item being sold.

Overall, the work of Milgrom and Wilson has had a profound impact on economics, game theory, and auction theory, as well as practical applications in various industries. Their research has gained widespread attention in academia and has significantly influenced real-world practices, including government policy-making and corporate decision-making. Their groundbreaking research has advanced the field of economics and had a wide-ranging impact on other fields such as computer science, engineering, and management. Their work will continue to be an essential reference for researchers and practitioners seeking to improve their understanding of the complex mechanisms and dynamics of auctions and markets.

## C.5 Other Related Research

In the context of art auctions, the Mei Moses Fine Art Index is noteworthy. Established in 2001 by Jianping Mei and Michael Moses, the index employs a repeat-sales methodology to track auction prices of the same artworks over time [130, 131]. It provides a structured and precise representation of art market trends based on extensive auction data. However, limitations include lack of liquidity and transparency in some art markets, hindering data collection for certain artworks, and the inability to capture all market changes due to other influencing factors.

## C.6 Conclusion

This appendix has provided a comprehensive review of auction theory, highlighting its evolution and key contributions from various economists and researchers. Understanding the theoretical foundations and cognitive aspects of decision-making in auctions enriches the analysis and modeling of auction mechanisms, particularly in the context of AI-driven simulations and behavioral studies.