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A Three-Party Dynamic Pricing Mechanism for Customized Data Products Based on the Stackelberg Game and Bargaining Model

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Abstract: In the era of big data, breaking down data silos to enable efficient data transactions has become essential, with the fairness and transparency of pricing mechanisms being paramount. This study addresses these challenges by introducing a novel tripartite pricing model for customized data products that integrates the Stackelberg and bargaining game frameworks. By designing distinct utility functions for buyers, sellers, and the platform, the model effectively aligns the varying objectives of each participant. A dynamic adjustment mechanism further enhances this model by adaptively recalibrating the guidance price and pricing range based on real-time updates to buyer budgets and seller offers, thus ensuring fairness and responsiveness throughout the negotiation process. Experimental simulations comprising 100 transaction rounds across diverse buyer–seller profiles validate the model's effectiveness, achieving a transaction success rate of 92.70% with an average of 6.86 bargaining rounds. These findings underscore the model's capacity to optimize transaction outcomes, promote pricing equity, and enhance bargaining efficiency. The proposed model has broad applications in sectors such as finance, healthcare, and e-commerce, where precise data pricing mechanisms are essential to maximize transactional value.

Keywords: customized data products; tripartite pricing model; Stackelberg game; bargaining game; dynamic adjustment mechanism

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1. Introduction

The rapid advancement of the digital economy has elevated data as a pivotal resource, driving transformative changes across various sectors. Fueled by big data and artificial intelligence, demand for personalized and customized data products is surging, creating new challenges for existing pricing models. The complexity of establishing effective pricing strategies in this multi-party market has become a focal issue for both academia and industry. Traditional models tend to concentrate on factors like data quality, scarcity, and market demand, often overlooking the potential of game theory in addressing transaction dynamics [1]. Specifically, in three-party transactions involving platforms, buyers, and sellers, achieving an equitable balance between all stakeholders' interests to improve transaction success rates remains a critical yet unresolved challenge.

In recent studies, various researchers have proposed models aimed at addressing these challenges. Recent studies have sought to develop data pricing models that consider various characteristics intrinsic to the data themselves. For instance, Yu and Zhang proposed a bilevel mathematical programming model that emphasizes the role of data quality by integrating quality dimensions and interactions into pricing.However, the model's limited consideration of data dimensions restricts its applicability across diverse demands and market scenarios [2]. Xuemei Li, on the other hand, developed models that examine the impact of data attributes like scarcity, non-competitiveness, and non-exclusivity on pricing outcomes, adapting pricing strategies to different market structures [3]. Although Li's models capture multiple data dimensions, they are limited by a narrow focus on data characteristics, lacking comprehensive insights into buyer–seller dynamics. Tian et al. advanced a Shapley value-based framework designed to facilitate interaction in tri-party data markets, specifically targeting scenarios that require boundary-setting for data prices [4]. However, this framework's static nature limits its adaptability, particularly under conditions of real-time demand fluctuations and privacy considerations within data markets. These contributions have established groundwork for data pricing; however, limitations persist when applied to customized data products within multi-party transactional environments.

Building upon this foundation, other researchers have introduced pricing models incorporating utility and game-theoretic principles to optimize outcomes for all participants in data transactions. Inegbedion et al. developed a pricing model for Nigeria's GSM data services market using a game-theoretic approach, introducing a Nash equilibrium strategy where MTN and its competitors adopt different pricing tactics to achieve Pareto efficiency [5]. However, this study is limited by its use of a zero-sum game model, focusing solely on maximizing service providers' payoffs without achieving transaction fairness, and it applies a static pricing model that overlooks adjustments in a dynamic market environment. Liu Jin and colleagues combined utility theory with the Stackelberg game framework, aiming to maximize benefits for both data providers and consumers by considering both parties' utilities, though their exploration of the bargaining process remains relatively limited [6]. In the IoT context, Takuya Yoshihiro and collaborators proposed a real-time data stream pricing model that employs mixed-integer linear programming to address seller competition and buyer demand, yet it does not fully capture the price negotiation process between buyers and sellers [7].

Despite significant progress and notable achievements, there remain substantial research gaps in addressing the complex dynamics and evolving demands of customized data product markets, especially in multi-party contexts. Existing methods often fall short of integrating the intrinsic value of data with the behavior and utility of both buyers and sellers, while simultaneously adapting to market trends for dynamic pricing adjustments. The challenge lies in developing comprehensive approaches that balance these dimensions—capturing data value, optimizing the utility of all stakeholders, and maintaining responsiveness to shifting market conditions. Addressing these aspects is critical for advancing the theoretical and practical frameworks of data pricing and remains an open area for further investigation.

This paper addresses key limitations in current data pricing models by proposing a tripartite pricing framework that integrates the Stackelberg and bargaining game theories, specifically tailored to meet the complexities of customized data product transactions. Traditional models often fall short of balancing fairness and efficiency in the face of dynamic market conditions. By leveraging the Stackelberg game, this framework establishes a hierarchical structure, positioning the platform as the leader that strategically guides interactions between buyers and sellers. Under the platform's supervision, buyers and sellers engage in a bargaining game to determine the final transaction price, ensuring that it reflects the interests of both parties. This dual-layered approach addresses the unique requirements of multi-party data transactions by creating a structured, sequential decision-making process that enhances both fairness and adaptability.

The primary objectives of this combined Stackelberg–bargaining model are to develop a balanced pricing strategy, enable dynamic price adjustments, and optimize transaction success rates, each directly addressing limitations identified in prior research. By employing the Stackelberg game for initial price guidance and the bargaining game for real-time negotiation, this model seeks to mitigate the inflexibility and low adaptability found in conventional pricing mechanisms. It is hypothesized that this sequential approach will significantly enhance market efficiency, particularly in accelerating transaction processes and improving success rates. Additionally, this study extends academic understanding by expanding the application of game theory to data pricing, offering a practical framework for platforms managing complex multi-party negotiations.

Each section of this paper aligns with these objectives. For instance, Section 4 integrates both the bargaining process and the dynamic adjustment mechanism, demonstrating how this dual framework continuously adapts to real-time market shifts. This innovative use of game theory not only advances theoretical knowledge but also provides platforms with an adaptable pricing tool for a variety of transaction scenarios, making it especially valuable for customized data markets.

The core goals of this study are as follows: (1) to construct a tripartite pricing model tailored for the customized data product market, (2) to validate the model's effectiveness and stability under different market conditions via simulations, and (3) to explore its potential applications in real-world markets. The hypothesis posits that in a multi-party transaction environment, a pricing model based on the Stackelberg and bargaining games can significantly enhance both market efficiency and transaction success.

To achieve these objectives, the methodology combines game theory with experimental economics. First, a Stackelberg–bargaining-based pricing model is constructed, with essential parameters determined through theoretical analysis. Subsequently, simulation experiments assess the model's performance and adaptability across diverse market conditions. Based on these findings, we discuss potential applications of the model and propose directions for further refinement.

This research contributes to academia by introducing an innovative pricing framework that merges the Stackelberg and bargaining game theories for customized data product transactions, thereby expanding the application of game theory in data pricing. Practically, this model offers effective pricing strategies for enterprises, improving market efficiency in data transactions and showing significant potential for real-world applications.

The structure of this paper is as follows:

- Section 2 presents the proposed tripartite pricing model, outlining the foundational principles and framework.
- Section 4 introduces the dynamic adjustment mechanism, detailing how pricing adapts to market shifts in response to changing conditions.
- Section 5 integrates the bargaining process within the context of the dynamic adjustment mechanism, describing their combined roles in determining the transaction price.
- Section 6 describes the experimental setup and methodology, providing a foundation for testing and validation under various market scenarios.
- Section 7 compares the results achieved using the proposed model against alternative methods, highlighting the model's effectiveness and adaptability.
- Section 8 concludes this study, summarizing key findings and suggesting directions for future research.

2. Three-Party Game Model

This paper proposes a three-party pricing model that combines the Stackelberg and bargaining game theories to establish a fair and efficient pricing mechanism for customized data products. The model aims to balance the interests of the buyer, seller, and platform, with the anticipated outcome of enhancing transaction success rates and improving fairness in pricing.

2.1. Definitions of Key Terms

Guidance price: The guidance price is an initial reference price set by the platform based on historical data, market conditions, and product demand complexity. In the absence of historical data, the platform will use alternative methods, such as market surveys, to fill in data gaps. It serves as a benchmark that guides both buyer and seller negotiations, providing a starting point that reflects current market trends and aids in aligning expectations. The guidance price is subject to dynamic adjustments by the platform in response to buyer and seller quotes, as well as variations in market demand and supply, to better reflect real-time transaction contexts.

Guidance price range: The guidance price range defines the permissible price interval within which buyer and seller negotiations occur. This range is dynamically adjusted by the platform as a function of market volatility, supply–demand shifts, and the historical behavior of quotes. Through real-time data analysis, the platform ensures that the guidance price range remains aligned with current market conditions, aiming to enhance transaction fairness and success rates.

Buyer utility: Buyer utility quantifies the buyer's satisfaction derived from the transaction and is expressed as the difference between the buyer's valuation of the customized data product and the final transaction price. A higher buyer utility indicates that the buyer perceives the purchase as favorable, which is essential in enhancing the buyer's participation and engagement in the bargaining process.

Seller utility: Seller utility reflects the seller's gain from the transaction, defined as the difference between the final transaction price and the seller's marginal cost of providing the customized data product. Higher seller utility indicates a profitable outcome, which incentivizes sellers to engage in price negotiations while balancing their own cost considerations against market expectations.

Platform Utility: Platform utility represents the combined benefit the platform obtains from a successful transaction, mathematically defined as the product of buyer utility and seller utility. This formulation ensures that any increase in either buyer or seller utility contributes equally to platform utility, reinforcing the platform's impartiality and commitment to fairness. By balancing buyer and seller satisfaction, the platform fosters a fair trading environment. Dynamic adjustments to guidance prices and price ranges by the platform aim to optimize both buyer and seller outcomes, ultimately enhancing platform utility in alignment with current market conditions and equitable transaction standards.

Bargaining power: Bargaining power indices play a crucial role in this three-party game model by quantifying each participant's relative influence within the negotiation framework. For buyers, the index reflects their influence relative to sellers' offers, while for each seller, it indicates their standing both in relation to the buyer's budget and to competing sellers' quotes. In a multi-party bargaining scenario, this index guides each party's pricing decisions, influencing whether they adjust their budget or offer, hold their position, or withdraw from negotiations. By quantifying bargaining power, these indices facilitate an understanding of each participant's strategic advantage and potential leverage, fostering stability and efficiency in the transaction process.

Optimal transaction price: The optimal transaction price is the price at which the buyer and seller reach an agreement that maximizes joint utility under the constraints of the guidance price and price range. It represents an equilibrium where both parties' utilities are sufficiently high, ensuring a mutually beneficial outcome and an efficient allocation of resources. The optimal transaction price is influenced by the platform's pricing guidance, buyer and seller utility functions, and prevailing market dynamics.

2.2. Roles of the Three Parties

2.2.1. Role of the Platform

The platform acts as the leader in the game, responsible for regulating buyer and seller behaviors to ensure fairness and impartiality throughout the transaction. To maintain a fair marketplace, the platform actively monitors buyer and seller actions, promptly addressing any undesirable behaviors, such as manipulative bidding, intentional misinformation, or attempts to circumvent the established price range. This oversight contributes to a transparent and orderly negotiation environment, fostering trust among participants.

The platform dynamically adjusts the reference price based on buyer and seller budgets and quotes, as well as the previous round's reference price. In terms of the price range, the platform applies a dynamic adjustment mechanism that incorporates changes in market supply and demand, bid behaviors of both parties, and observed market volatility. As bargaining rounds progress, the platform continuously analyzes historical data in real-time, allowing it to refine the price range to more accurately reflect current market conditions.

The utility of the platform is defined as the product of buyer and seller utilities, ensuring that utility increases for both buyers and sellers contribute equally to the platform's utility. This approach guarantees that the platform's actions promote fairness and impartiality, balancing both parties' interests and enhancing transaction success rates within an equitable framework.

2.2.2. Role of the Buyer

The buyer enters the game by submitting customized data product requirements along with a budget, aiming to purchase the desired data product at the lowest possible price. The buyer must operate within the price range set by the platform, balancing their own budget constraints with the guidance price. The assumptions in this model include that buyers may have varying levels of risk tolerance, which influences their approach to negotiation and their willingness to deviate from the guidance price.

2.2.3. Role of the Seller

The seller participates in the game with the objective of maximizing their selling price for the data product. Sellers are constrained by their cost structures and the platform's guidance price and price range. Additionally, sellers are assumed to have individual thresholds for risk tolerance, which influence how they adjust their quotes during negotiation. Sellers must strategically consider their proximity to the guidance price while managing cost-related constraints to remain competitive in the bargaining process.

2.3. Theoretical Rationale for Utility Functions

In this model, the Mean-Variance Utility (MVU) framework provides an effective means of quantifying each party's decision-making process by balancing expected returns and associated risks, which are key factors in the uncertain environment of customized data product transactions. Given the variability in pricing and market dynamics, this framework helps to model the trade-offs that both buyers and sellers face, making it particularly suited to capturing the utility functions of both parties. The MVU framework's integration with bargaining power indices also allows each party to dynamically adjust their negotiation strategies, reflecting changes in relative influence over the course of the transaction.

Risk and return considerations are central to each party's utility. For buyers, risk primarily involves price uncertainty and the potential of exceeding their budget, while return reflects the satisfaction derived from acquiring a product that aligns with their valuation at a favorable price. Sellers face risk in the form of demand uncertainty, as they may miss an opportunity to sell if the quoted price does not align with the buyer's budget, whereas return is generated through successful sales above their marginal costs. The platform, in ensuring transaction stability and fairness, also considers collective utility, aiming to align both buyer and seller satisfaction with real market conditions.

3. Definition of Utility Functions

The utility functions for the buyer, seller, and platform are structured to capture each participant's motivations and constraints within the bargaining model. This approach leverages the mean-variance utility framework, which effectively balances risk and return—a critical consideration for negotiations involving budget constraints and pricing flexibility [8,9]. Additionally, bargaining power indices are integrated to model each party's influence in the bargaining process.

3.1. Buyer's Utility Function

The Mean-Variance Utility (MVU) framework encapsulates the balance between expected returns (mean) and associated risks (variance), where risk is measured based on return variability. Within this framework, expected return denotes the projected gain, while variance reflects potential fluctuations, thereby indicating the level of risk inherent to the transaction.

In this study, the transaction price p represents the intrinsic value of the customized data product, contributing to utility for both the buyer and seller. The buyer's expected return E_{buyer} is expressed as the ratio $\frac{p}{b}$, where b denotes the buyer's budget. This formulation not only connects the transaction price to the buyer's budgetary constraints but also encapsulates the buyer's anticipated return within these constraints, achieving a balance between expected utility and associated risk [10].

The buyer's expected return E_{buyer} is defined as follows:

$$E_{\text{buyer}} = \frac{p^2}{b} \tag{1}$$

where p represents the platform's guidance price, serving as a benchmark, and b denotes the buyer's budget. Here, the mean-variance utility framework is well-suited, as it captures the buyer's need for an optimal trade-off between cost (budget) and anticipated product value.

The risk term in the buyer's utility function quantifies the perceived alignment between the buyer's budget b and the guidance price p, with $(b - p)$ representing this deviation. A smaller deviation implies a close alignment between budget and guidance price, suggesting lower perceived risk, whereas a larger deviation indicates misalignment, signaling higher perceived risk. To capture this relationship, the deviation is squared and normalized by $2\sigma^2$, where σ denotes the standard deviation derived from the guidance price range $[p_{\min}, p, p_{\max}]$, reflecting market volatility. A higher σ indicates a broader acceptable price range, thereby amplifying the risk associated with greater budget deviation.

The decay in perceived risk as the budget b approaches the guidance price p is modeled by the exponential function $e^{-\frac{(b-p)^2}{2\sigma^2}}$. For minor deviations, this term approaches 1, denoting minimal risk. As the deviation grows, the exponential term quickly decreases towards zero, indicating a substantial increase in perceived risk.

This buyer's risk term thus encapsulates the uncertainty of achieving a favorable price in relation to market volatility and the alignment of the buyer's budget with the guidance price. It is modeled using a normal distribution with mean $\mu = p$ and standard deviation σ, grounded in the guidance price range $[p_{\min}, p, p_{\max}]$. The buyer's risk term can be defined as follows:

$$1 - e^{-\frac{(b-p)^2}{2\sigma^2}} \tag{2}$$

The function indicates that the buyer's perceived risk decreases as the alignment with the guidance price tightens, enhancing the buyer's confidence in value realization. We have clarified that buyer risk must be considered even when the buyer's budget exceeds the platform price. In such cases, the buyer may purchase the data product at a price higher than its intrinsic value, leading to a utility loss. Based on the mean-variance utility theory, and in conjunction with the previously defined E_{buyer}, the complete utility function is as follows:

$$V_{\text{buyer}} = (1 - e^{-\frac{(b-p)^2}{2\sigma^2}}) \cdot |p - b| \tag{3}$$

This expression captures the buyer's exposure to price deviations from the guidance price, decreasing as b converges on p. For practical interpretation, the function indicates that the buyer's perceived risk diminishes with a tighter alignment to the guidance price, fostering confidence in value realization. The complete utility function is then as follows:

$$u(b) = \frac{p^2}{b} - k \cdot \left(1 - e^{-\frac{(b-p)^2}{2\sigma^2}}\right) \cdot |p - b| \tag{4}$$

where k is the risk aversion coefficient, reflecting the buyer's sensitivity to price deviations.

3.2. Seller's Utility Function

Analogous to the buyer's utility, the seller's function also incorporates the mean-variance utility framework to balance potential earnings with associated risks. The seller's expected return E_{seller} is defined as follows:

$$E_{\text{seller}} = \frac{o^2}{p} \tag{5}$$

where o is the seller's quoted price. This formulation interprets the seller's return in terms of maximizing price relative to the platform's guidance. The seller's risk component, capturing the likelihood of misalignment with buyer expectations, is represented as follows:

$$V_{\text{seller}} = \left(1 - e^{-\frac{(o-p)^2}{2\sigma^2}}\right) \cdot |o - p| \tag{6}$$

Here, the risk term decreases as the seller's quoted price aligns with the platform's guidance price, indicating lower uncertainty about buyer acceptance. Thus, the seller's utility function is given as follows:

$$u(o) = \frac{o^2}{p} - k \cdot \left(1 - e^{-\frac{(o-p)^2}{2\sigma^2}}\right) \cdot |o - p| \tag{7}$$

By leveraging the mean-variance utility framework and accounting for bargaining power, the buyer's and seller's utilities dynamically reflect both risk tolerance and the potential return, leading to a more stable and efficient transaction process. The use of these utility functions within a well-defined price range promotes equilibrium, guiding each participant's decision-making toward optimizing their respective utilities under realistic market conditions.

3.3. Bargaining Power Indices

The bargaining power indices of the buyer and seller quantify their negotiation leverage, which influences the final outcome of the negotiation.

3.4. Buyer's Bargaining Power Index

The Buyer's Bargaining Power Index (BPI) reflects the buyer's flexibility and the ratio of active sellers in the market:

$$\alpha = \frac{1}{2} \times \max\left(0, \frac{b - p_{\min}}{p_{\max} - p_{\min}} + \frac{n_a}{n}\right) \tag{8}$$

Here, $\frac{n_a}{n}$ represents the ratio of active sellers n_a (the number of sellers still participating in the negotiation) to the initial number of sellers n, reflecting the relative strength of the buyer in the negotiation. The variable b represents the buyer's budget, while $p_{\min}$ and $p_{\max}$ represent the minimum and maximum values of the platform's price guidance range, respectively.

3.5. Seller's Bargaining Power Index

The Seller's Bargaining Power Index (SPI) is formulated based on the seller's quote relative to the market conditions [11]:

$$\beta_i = \frac{1}{2} \times \max\left(0, \frac{o_{\max} - o_i}{\sum_{j=1}^{n_a}(o_{\max} - o_j)} + \frac{n}{n_a}\right) \tag{9}$$

Here, $\frac{n}{n_a}$ represents the ratio of the initial number of sellers n to the number of active sellers n_a, indicating the seller's leverage under competitive conditions. The variable $o_{\max}$ represents the maximum offer price made by the sellers, and o_i represents the specific price quoted by seller i.

3.6. Justification of Factors in the Formulas

1. Ratio of active sellers to initial sellers $\left(\frac{n_a}{n}\right)$: This ratio reflects the competitive environment in the market. When more sellers remain active (i.e., when $\frac{n_a}{n}$ is high), the buyer has more options and thus greater bargaining power. In contrast, if many sellers exit the negotiation, the remaining sellers face less competition, thereby increasing their individual bargaining leverage. This factor effectively captures the dynamic nature of the market.
2. Relative price factors $\frac{b-p_{\min}}{p_{\max}-p_{\min}}$ and $\frac{o_{\max}-o_i}{\sum_{j=1}^{n_a}(o_{\max}-o_j)}$:
   - For buyers, $\frac{b-p_{\min}}{p_{\max}-p_{\min}}$ captures the buyer's budget b relative to the platform's price guidance range, which is defined by $p_{\min}$ (the minimum price) and $p_{\max}$ (the maximum price). If the buyer's budget b is close to the minimum price $p_{\min}$, their bargaining power is weaker, and vice versa.
   - For sellers, $\frac{o_{\max}-o_i}{\sum_{j=1}^{n_a}(o_{\max}-o_j)}$ reflects the seller's offer o_i relative to the maximum offer $o_{\max}$ made by other active sellers. Sellers who offer prices close to the maximum offer $o_{\max}$ tend to lose some of their bargaining power.

A higher bargaining power index (BPI or SPI) thus indicates a more advantageous position in the negotiation. Buyers can leverage their access to multiple sellers and relatively stronger financial positions, while sellers benefit from reduced competition or competitive pricing to assert stronger negotiation leverage.

3.7. Assumptions in the Bargaining Power Model

The model is based on the following assumptions:

1. Market conditions and participant numbers: The model assumes stable market conditions, where the number of active participants accurately reflects the market dynamics. If the market conditions change rapidly, the indices may fail to adjust in real-time, reducing their accuracy.
2. Rationality of buyers and sellers: The indices assume rational behavior from both buyers and sellers, meaning that each participant aims to maximize their own utility. In cases of irrational behavior, the bargaining power indices may not align with actual negotiation outcomes.
3. Initial price guidance: The model assumes that the price guidance range $p_{\min}$ to $p_{\max}$ accurately reflects the market conditions. If the price guidance is inaccurate, the expectations of buyers and sellers may diverge from the actual market conditions, distorting the bargaining power indices.

3.8. Limitations of the Bargaining Power Model

- **Sensitivity to outliers:** The bargaining power indices can be distorted by extreme values in offers, especially in markets with high variability.
- **Seller differentiation:** The model does not account for qualitative differences between sellers, such as brand value or service quality, which may influence bargaining power in real-world negotiations.

3.9. Platform's Utility Function

The platform's utility function ensures neutrality by being the product of the buyer's and seller's utilities, weighted by their respective bargaining power indices:

$$u(p) = u(b)^{\alpha} \times u(o)^{\beta} \tag{10}$$

According to the bargaining Nash equilibrium theory, when the product of the buyer's and seller's utilities—i.e., the platform's utility—is maximized, the payoffs for all parties reach their optimal levels, and the model achieves its best state [12,13]. In this framework, the platform's utility function is raised to the power of the respective bargaining power indices, ensuring fairness and impartiality without favoring any party.

This construction reflects the platform's role as a neutral facilitator, ensuring that the utilities of both the buyer and the seller are proportionally weighted according to their bargaining power, thereby maintaining fairness throughout the transaction.

3.10. Summary and Justification of Utility Function Construction

The model provides a structured and fair framework for pricing customized data products by integrating mean-variance utility functions and bargaining power indices. In practical applications, the model can be used in data marketplace platforms, e-commerce systems, and digital services industries. It addresses issues such as information asymmetry, price fluctuations, and market inefficiencies by dynamically adjusting prices. By precisely modeling the utilities and bargaining powers of both buyers and sellers, the model ensures fairness in transactions and market transparency, promoting efficient market operations and long-term trust.

The model is based on the following key assumptions:

- **Market conditions and participant numbers:** It is assumed that market conditions are stable and that the number of participants accurately reflects market dynamics. If market conditions change rapidly, the model may fail to adjust in real-time, leading to a reduction in the accuracy of the indices.
- **Rational behavior:** The model assumes that both buyers and sellers act rationally, seeking to maximize their respective utilities. In the case of irrational behavior, the bargaining power indices may not align with the actual negotiation outcomes.
- **Price guidance range:** The model assumes that the price guidance range, from $p_{\min}$ to $p_{\max}$, accurately reflects market conditions. If the price guidance is inaccurate, the expectations of the buyers and sellers may diverge from actual market conditions, distorting the bargaining power indices.

These assumptions form the foundation of the model's validity and effectiveness. Any deviation from these assumptions in practical applications may affect the accuracy of the model's predictions.

4. Dynamic Adjustment Mechanism for the Platform's Guidance Price and Price Range

The platform's dynamic adjustment mechanism for guidance price and price range is designed to enhance market fairness and increase transaction success rates, particularly for customized data products. This mechanism addresses unique challenges posed by the distinct characteristics of each transaction and the limited relevance of historical transaction data. Key aspects of this approach include the following:

- **Adaptation to demand characteristics:** Customized data products often exhibit specific demand features that do not fully reflect their intrinsic market value, making dynamic adjustment essential.
- **Real-time price adjustment:** The mechanism operates within the bargaining process between buyers and sellers, using market conditions along with budget and quote information from both parties to rationally adjust the guidance price and its range in real time.
- **Role as a market leader:** By closely tracking market trends, the platform maintains its role as a leader in the Stackelberg game framework, supervising buyer and seller actions to facilitate fair, reasonable, and transparent transactions.

4.1. Anti-Interference Mechanisms

To mitigate the impact of extreme values on price adjustments, the platform employs the following anti-interference mechanisms:

- **Median selection**: The median is used instead of the mean to minimize the influence of outliers, thereby providing a more robust central tendency for price adjustments.

- **Outlier exclusion**: Extreme outliers are systematically removed prior to adjustments. We use a statistically based criterion, identifying data points that deviate more than three standard deviations from the median as outliers and excluding them to prevent skewing the adjustment results.
- **Data trimming**: Prior to calculating the median or mean, the top and bottom 5% of both buyer budgets and seller quotes are trimmed. The 5% threshold is chosen because, in highly volatile market conditions, these extreme values frequently contain noise or outliers that may distort pricing decisions. This percentage, however, is not fixed; it can be dynamically adjusted based on market conditions. For instance, in high-volatility markets, the trimming percentage may be increased to further limit the influence of extreme values, while in stable market conditions, it may be reduced to preserve more of the data for analysis.

4.2. Adjustment Mechanisms

The platform's guidance price and price range are updated in each round of the game as follows:

4.2.1. Guidance Price Adjustment

The guidance price for the next round, P_{t+1}, is calculated using the median of the buyer's budget M_B and the median of the sellers' quotes M_S, weighted by the dynamically adjusted parameter α. Here, α serves as a regulatory factor, which the platform adjusts dynamically based on market fluctuations and the relative bargaining power of the buyer and sellers, ensuring that the guidance price reflects current market conditions and the strength of negotiation positions.The calculation formula for the next round of guidance price is as follows:

$$P_{t+1} = \alpha \cdot M_B + (1-\alpha) \cdot M_S \tag{11}$$

4.2.2. Price Range Adjustment

In the price range adjustment mechanism, the price range R_{t+1} is determined by the current guidance price P_t, seller quote volatility σ_S, buyer budget volatility σ_B, and the dynamically adjusted coefficients k_1 and k_2:

$$R_{t+1} = [P_t - k_1 \cdot \sigma_S - k_2 \cdot \sigma_B, P_t + k_1 \cdot \sigma_S + k_2 \cdot \sigma_B]$$

where σ_S represents the standard deviation of seller quotes, indicating seller quote volatility. Higher values of σ_S result in a wider price range to accommodate fluctuations in seller pricing. σ_B represents the standard deviation of buyer budgets, capturing buyer budget volatility. Higher σ_B values imply greater uncertainty in buyer demand, necessitating an expanded price range to account for buyer budget variability. k_1 and k_2 are dynamic adjustment coefficients applied to σ_S and σ_B, respectively. They are adjusted based on market conditions and the relative bargaining power of buyers and sellers. These coefficients serve to enhance the flexibility of price adjustments, with the goal of promoting fairness and equity within the model.

The dynamic adjustment of k_1 and k_2 enables the platform to rationally expand or contract the guidance price range based on actual bargaining power, thus balancing the interests of both buyers and sellers and fostering fairness and transparency in market transactions.

In addition, k_1 and k_2 act as dynamic adjustment factors that control the responsiveness of the price range to seller quote volatility and buyer budget volatility:

k_1 adjusts the sensitivity of the price range to seller quote volatility. In markets with high seller quote volatility, increasing the value of k_1 can expand the price range to accommodate a wider variety of seller quotes. k_2 adjusts the sensitivity of the price range to buyer budget volatility. In markets where buyer budgets are highly variable, increasing k_2 broadens the price range to better account for the diversity in buyer budgets.

By flexibly adjusting k_1 and k_2, the platform can appropriately expand or contract the price range to match current market volatility characteristics, thus adapting to the demands of both buyers and sellers and ensuring fairness and rationality in the transaction process.

4.3. Dynamic Weight Parameters and Adjustment Factors

To dynamically adjust α, k_1, and k_2 in response to market conditions, the platform continuously monitors market volatility using specific indicators. "Market volatility" is defined as the extent of variation in recent transaction data, particularly in terms of buyer budgets and seller quotes. The primary indicators used to assess market volatility include:

- **Standard deviation of recent prices**: The standard deviation of historical transaction prices is calculated over a moving time window. A high standard deviation indicates greater price fluctuations, which signifies a volatile market.
- **Range of buyer budgets and seller quotes**: The platform assesses the spread between the highest and lowest buyer budgets and seller quotes in recent transactions. A widening spread suggests increasing volatility.
- **Transaction volume fluctuation**: Significant changes in transaction volume over short periods are also considered indicative of volatility, as they often reflect shifts in market demand or supply conditions.

The platform categorizes the market as "volatile" or "stable" based on threshold values for these indicators. For instance, if the standard deviation of recent prices exceeds a predefined threshold, or if the range between buyer budgets and seller quotes widens beyond a certain limit, the platform identifies the market as volatile. In response:

- When market volatility is high, α is reduced, giving less weight to the previous round's guidance price and allowing current buyer and seller input to influence the new price more directly.
- k_1 and k_2 values are increased to widen the guidance price range, providing a larger buffer to accommodate price fluctuations and reduce the likelihood of abrupt price changes that could destabilize negotiations.
- In stable market conditions, α is increased, giving greater weight to the previous guidance price, while k_1 and k_2 are reduced to narrow the price range, facilitating more precise pricing aligned with the steady market state.

This volatility-based adjustment mechanism enables the platform to adaptively balance stability and responsiveness, ensuring rational and fair pricing adjustments that are aligned with current market conditions.

4.4. Known Limitations

While the dynamic adjustment mechanism improves price fairness and transaction success, it has limitations. Under extreme market volatility, adjustments may lag, causing temporary misalignment with true market prices. In thin markets with few buyers or sellers, limited data can lead to less reliable pricing and increased susceptibility to outliers.

Extreme market volatility or thin markets with few buyers or sellers can lead to substantial adjustments in the α, k_1, and k_2 parameters, increasing the model's instability and uncertainty. These conditions amplify the impact on price and price range calculations, representing a primary limitation of the current model.

4.5. Summary and Practical Implications

The platform's dynamic adjustment mechanism realigns the guidance price and range in real time to reflect current market demand, minimizing the effects of outliers and outdated data. In practical markets, this approach enhances transaction fairness by aligning prices with actual market value, reducing imbalances caused by volatility or information asymmetry. Additionally, dynamic adjustments facilitate consensus between buyers and sellers, thereby increasing transaction efficiency.

In volatile markets, the mechanism broadens the price range to accommodate uncertainty, while in stable conditions, it narrows the range for greater pricing precision, effectively balancing fairness and efficiency.

5. Game Process

This game process supports the dynamic pricing mechanism for customized data products, integrating various components of the trading system. By analyzing buyer requirements, market conditions, and historical transaction data, the platform sets an initial price that adjusts dynamically through multi-round negotiations to ensure fairness and increase transaction success rates. The process unfolds in the following steps, and the pseudocode of the bargaining process can be found in Appendix A.

5.1. Step 1: Submission of Demand by Buyer

The buyer submits a set of data requirements to the platform, typically including essential specifications such as data quality, accuracy, consistency, completeness, accessibility, and privacy standards. Additionally, the buyer may specify personalized or customized requests, such as data complexity, degree of customization, and processing timeliness. The buyer also provides a maximum expected number of bargaining rounds to set constraints on the negotiation duration. These requirements form the basis for the platform's initial pricing and subsequent dynamic adjustments (see Figure 1).

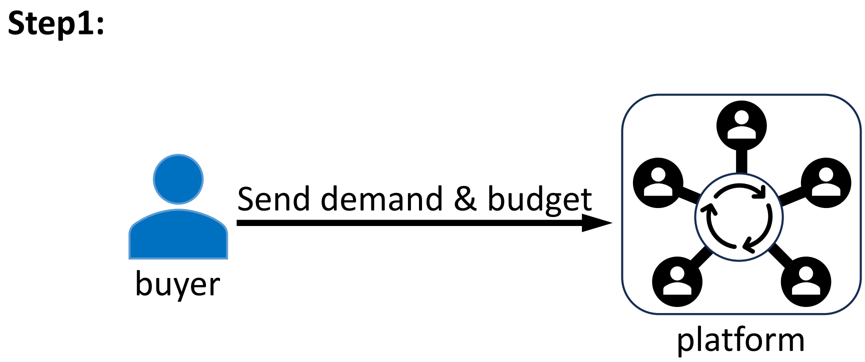

Figure 1. Submission of demand by buyer.

5.2. Step 2: Platform Sets Reference Price and Price Range

Based on the buyer's requirements, complexity, market conditions, and historical transaction data, the platform determines an initial reference price and corresponding price range. This initial setup is guided by a specific algorithm or logic that reflects current market trends (see Figure 2).

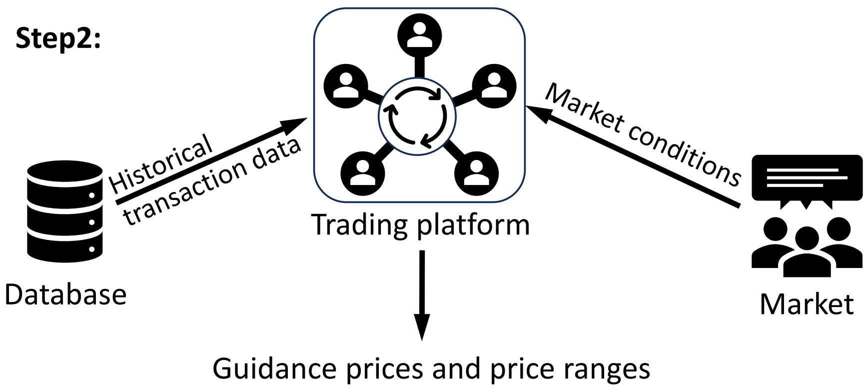

Figure 2. Platform sets reference price and price range.

5.2.1. Initial Price Setup Based on Data Attributes and Market Conditions

To determine a fair and adaptable initial pricing framework for customized data products, the platform dynamically computes the reference price P_{ref} and price range R_{price} based on critical factors such as data complexity, customization level, processing urgency, and privacy requirements. This multi-dimensional pricing mechanism allows the platform to align initial prices with the specific demands of buyers while reflecting current market conditions.

5.2.2. Reference Price Calculation

The reference price P_{ref} represents the core valuation of a data product and is derived through a weighted sum of the following components:

$$P_{ref} = \kappa \cdot C_d + \lambda \cdot U_c + \mu \cdot T_p + \nu \cdot S_p$$

where:

- C_d (complexity of data): Reflects the intrinsic complexity or specificity of the data product, taking into account factors such as the volume of data, processing difficulty, and expertise required.
- U_c (customization degree): Indicates the extent to which the data product meets the buyer's unique requirements, influencing its suitability for particular applications.
- T_p (timeliness of processing): Represents the buyer's urgency for data delivery; higher values correspond to expedited processing needs.
- S_p (privacy and security level): Measures the level of privacy and data security demanded by the buyer, especially important in cases where sensitive information is involved.

The parameters κ, λ, μ, and ν serve as weight coefficients, calibrated to capture current market conditions and buyer preferences. By adjusting these coefficients, the platform ensures that P_{ref} accurately reflects the inherent value of the data product in response to each transaction's specific requirements.

5.2.3. Price Range Determination

The initial price range R_{price} defines the flexible boundaries within which bargaining can occur, accommodating market dynamics and allowing for negotiation flexibility. The price range is calculated as follows:

$$R_{price} = \left[P_{ref} \cdot (1-\theta), P_{ref} \cdot (1+\theta)\right]$$

where θ represents a market volatility factor, which adjusts based on current demand–supply variations and market conditions. This factor provides a margin that facilitates smoother negotiations by offering a reasonable price range that reflects of prevailing market trends.

This pricing model thus provides an adaptive approach to setting the initial price and range, balancing transaction fairness and adaptability in a competitive data marketplace. By accounting for data-specific attributes and market conditions, the platform establishes a basis for dynamic, customized pricing that aligns with buyer expectations and optimizes transaction success.

5.3. Step 3: Publication and Seller Engagement

The platform announces the buyer's demand, reference price, and price range, inviting sellers to enter the bidding process and initiate competitive negotiations. Both parties reference the platform's guidance price, engaging in bargaining within the price range. The final price is determined by the interplay between the seller's quote and the buyer's budget. The platform adjusts the guidance price range to influence the bargaining strategies and ensure transaction fairness and price stability. (see Figure 3).

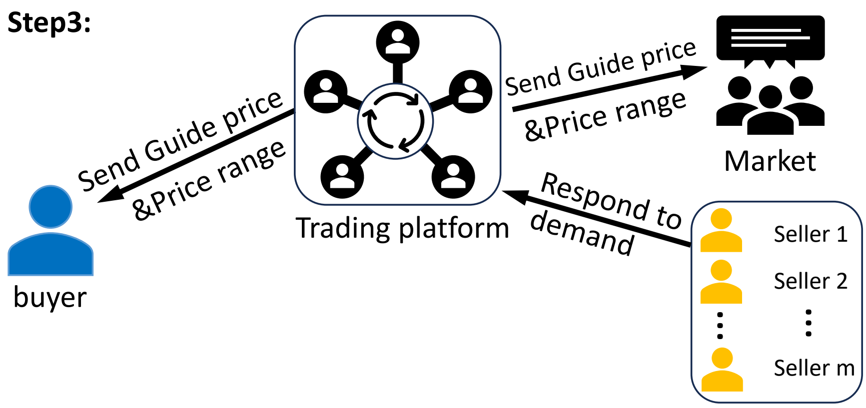

Figure 3. Publication and seller engagement.

5.4. Step 4: Multi-Round Negotiation

During the multi-round negotiation phase, both buyer and sellers engage by submitting their respective budgets and quotes. If no seller's quote falls below the buyer's budget in a given round, the negotiation is considered unsuccessful for that round, and the process proceeds to the next. In each round, the platform dynamically adjusts the reference price and price range based on the buyer's and sellers' submissions, along with market conditions, to guide the negotiation. To ensure convergence within a reasonable number of rounds, the platform applies a dynamic price range adjustment mechanism based on the buyer's maximum expected rounds. When the actual rounds approach or exceed this expected value, the price range narrows progressively to expedite an agreement. Furthermore, to prevent indefinite bargaining, the buyer's budget in each successive round cannot be lower than in the current round, and sellers are restricted from raising their quotes in subsequent rounds (see Figure 4).

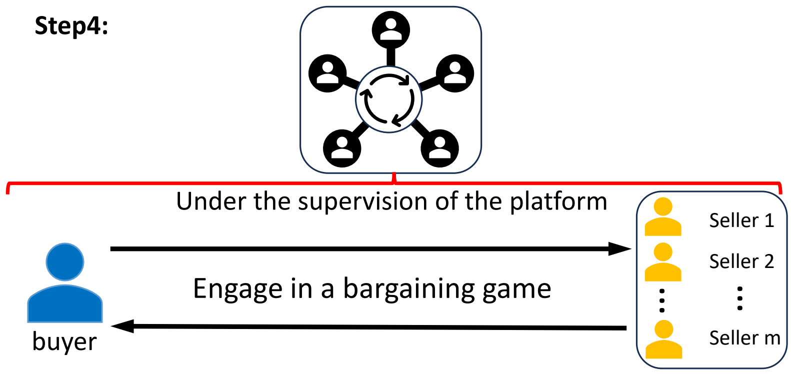

Figure 4. Multi-round negotiation.

5.5. Step 5: Exit Conditions

During the dynamic bargaining process, the game terminates if any of the following exit conditions are met, ensuring optimal resource allocation and maximizing utility:

1. **Buyer Exit Condition**
   The buyer exits the game if their utility value is less than or equal to zero, or if their bargaining power index falls to zero or below.
2. **Seller Exit Condition**
   Any seller exits the game if their utility value is less than or equal to zero, or if their bargaining power index declines to zero or below.
3. **Price Acceptance Condition**
   After the optimal transaction price is calculated, if either the buyer or any remaining seller rejects the proposed price, the game terminates.

These exit conditions prevent inefficient or unproductive bargaining rounds, enhancing transaction success rates while maintaining negotiation fairness and efficiency on the platform (see Figure 5).

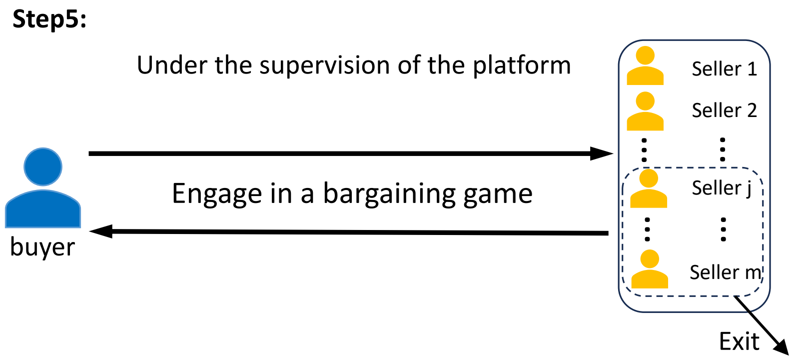

Figure 5. Exit criteria and continuation.

5.6. Step 6: Final Price Determination

When any seller's quote is below the buyer's current budget, the negotiation process ceases, and the platform proceeds to calculate the optimal transaction price. The platform searches within the price range [Seller's Quote, Buyer's Current Budget] to identify a price that maximizes its utility. The platform's utility is defined as the product of the buyer's and seller's utilities, each raised to the power of their respective bargaining power indices. Achieving the maximum platform utility represents an optimal allocation of utilities under the current conditions, thus reaching the Nash equilibrium solution for the bargaining game. This price is then identified as the optimal transaction price, ensuring utility maximization for all parties within a fair framework (see Figure 6).

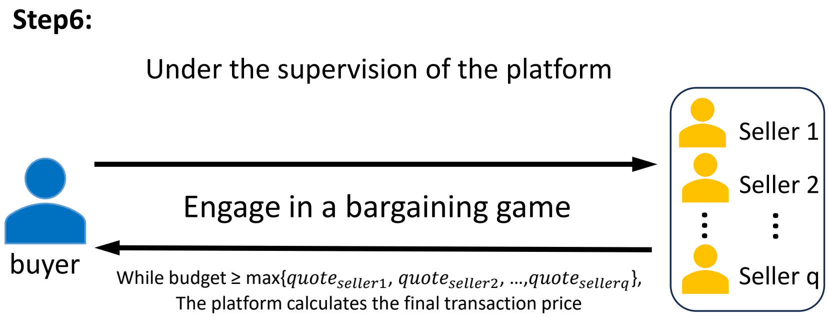

Figure 6. Final price determination.

External factors, such as market volatility or sudden shifts in buyer demand, may also impact the final price. These are addressed by adjusting the relevant parameters, ensuring that the final price remains optimal and fair even in changing market conditions.

5.7. Step 7: Transaction Completion

Upon acceptance of the final price by both parties, the platform facilitates the exchange of the customized data product. In case of a negotiation failure, the transaction concludes without a deal (see Figure 7). The platform may also offer options for renegotiation, alternative matches, or compensation if no agreement is reached, ensuring a seamless transaction experience.

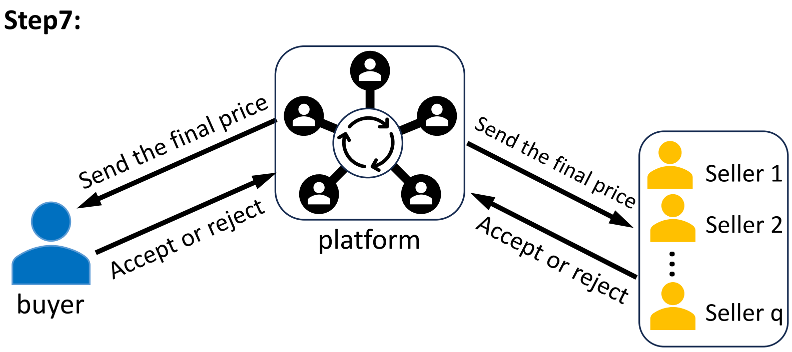

Figure 7. Transaction completion.

5.8. Customer Choice Mechanism in Case of Transaction Failure

In the event of a transaction failure, the platform allows customers to choose between an alternative matching option and a compensation policy to enhance post-failure satisfaction and improve service quality.

1. **Alternative Matching Option**
   The platform offers an alternative matching option for buyers whose transactions were unsuccessful, where the system searches for new sellers based on the buyer's specific needs and budget. This matching mechanism provides greater flexibility by identifying sellers who better align with the buyer's requirements, reducing the impact of transaction failure and improving service quality for customers without successful transactions. This mechanism thus enhances the overall transaction success rate on the platform.
2. **Compensation Policy**
   To maintain customer trust and satisfaction following a transaction failure, the platform can implement a compensation policy. For customers whose transactions are not completed, the platform may reward points or vouchers based on the level of effort and attempts to reach an agreement. These incentives encourage future transactions on the platform. Additionally, the platform may offer such customers priority in future matching opportunities, further enhancing the user experience and promoting loyalty.

By providing alternative matching and compensation options, the platform effectively mitigates the impact of transaction failures, increases transaction success rates, and improves customer satisfaction and loyalty.

5.9. Relevance and Applicability of Multi-Party Game Dynamics in Data Marketplaces

The multi-party game process outlined in this model has significant relevance in real-world data marketplaces or platforms, facilitating dynamic pricing of data products. By incorporating variables such as buyer budgets, seller quotes, and market conditions, the platform can adjust price ranges in response to varying demand and market dynamics, thereby enhancing fairness and transaction success rates.

This model assumes market volatility in data demand and supply, with clearly defined utility functions for buyers and sellers. To bolster reliability in practical applications, the platform incorporates data verification protocols and constraints to prevent manipulation by participants. Furthermore, the platform employs dynamic price and round adjustments to avoid monopolistic pricing and prolonged negotiations without agreement. This mechanism ensures transparency and fairness in transactions while optimizing the balance of interests among all parties involved.

6. Experimental Design and Simulation

6.1. Experimental Setup

The simulation-based experiments employ data generated under a normal distribution, chosen as an approximation for real-world demand, cost, and pricing characteristics observed in similar market contexts. A normal distribution, with its symmetrical properties and predictable variance, provides a robust foundation for modeling the randomness and variability often seen in market behaviors. Although real-world data may not always strictly follow a normal distribution, this assumption enables a simplified yet effective approach to analyze interactions within the model. Any deviation from real-world distributions is noted as a limitation, which could impact certain aspects of the results. For exact reproducibility, we use a fixed random seed, set to 100, ensuring consistency across experiments and enabling controlled testing conditions. Each experiment is repeated 1000 times to reduce the influence of outliers and to ensure result stability.

The platform's initial reference price is set to 1000, with a price range between 800 and 1200, chosen to reflect a balanced market scenario with typical fluctuation margins. Sensitivity analysis is conducted to evaluate the robustness of outcomes against variations in these parameters, ensuring that the results are not overly dependent on specific values. The buyer's risk aversion coefficient k_b is set to 3.5, representing moderate risk aversion, while the sellers' risk aversion coefficients k_s are randomly assigned within a range of 2 to 6 to capture the diverse risk tolerance levels that are common in practical market settings [14,15].

The number of participating sellers is set to 10, providing a balanced scenario for interaction and competition in the simulated market. Additional tests were also conducted with varying numbers of sellers to assess the scalability of the model and to observe the effects of seller participation on market dynamics.

6.2. Comparative Experiments

In addition to testing the proposed model, two comparative experiments are conducted to evaluate its performance relative to alternative pricing approaches. The design of these comparative experiments aims to demonstrate the effectiveness and unique contributions of the tripartite bargaining model, specifically by examining the platform's impact on pricing fairness, transaction success rate, and bargaining efficiency. Each experiment is described as follows (Table 1):

1. **Tripartite bargaining model:** This experiment evaluates the proposed model, where the platform, buyer, and sellers actively engage in bargaining. The platform participates not only by setting a reference price and price range but also by engaging in the bargaining process, intending to balance fairness and optimize platform utility. This configuration is expected to showcase the advantages of platform involvement in terms of transaction success and price fairness.
2. **Stackelberg-only model:** This experiment features a modified tripartite game that excludes the bargaining process. Here, the platform acts solely as a leader by setting a reference price and range, while buyers and sellers submit their budget and bids independently. This setup provides a baseline for comparing the effects of bargaining, allowing us to observe whether direct negotiation enhances transaction success and fairness compared to the Stackelberg-only model.
3. **Bilateral bargaining model:** This experiment simulates a traditional bilateral bargaining process solely between the buyer and sellers, without the platform's intervention. In this configuration, the final transaction price is determined through direct negotiation. This setup serves to highlight the unique role of the platform in facilitating fair and efficient bargaining, allowing us to compare results and analyze the platform's effects on bargaining dynamics, transaction success, and price fairness.

The goal of these comparative experiments is to demonstrate how the platform's active participation in the bargaining process influences key outcomes. We expect that the tripartite bargaining model will outperform the other two setups by achieving higher transaction success rates, enhanced price fairness, and improved bargaining efficiency, thus validating the practical relevance of our model.

Table 1. Comparison of experiments

Experiment	Exp. 1	Exp. 3	Exp. 2
Game model	Stackelberg + bargaining	Stackelberg	Bargaining
Third-party platform	Yes	Yes	No
Initial guidance price	Yes	Yes	No
Dynamic adjustment	Yes	No	No
Game process	Yes	No	Yes
Game rounds limit	Yes	No	No

6.3. Evaluation Metrics

To comprehensively assess the performance of each model, the following metrics are applied:

1. **Transaction success rate:** This metric calculates the proportion of successful transactions under each set of game rules, with a transaction being deemed successful if all parties reach a mutually acceptable agreement.
2. **Price fairness:** Price fairness is quantified by measuring the deviation of the final transaction price from the market average, providing an indication of the fairness of the pricing outcomes across simulations.
3. **Bargaining efficiency:** Efficiency is evaluated by counting the number of rounds required to reach a transaction, where fewer rounds indicate higher efficiency and quicker convergence to an agreed price.
4. **Balance of success rate and efficiency:** This composite metric assesses overall model performance by balancing the transaction success rate and bargaining efficiency within a set round limit (e.g., within ten rounds), utilizing a weighted calculation to reflect both factors in a single, integrated measure.

In the second experiment, discussions related to bargaining rounds are omitted, as there is no negotiation process. Statistical analyses, including significance testing and confidence intervals, were conducted to validate these metrics across different models, enabling precise comparisons in success rates and fairness outcomes. The results, along with sensitivity analyses of key parameters, are visualized using tables and graphs, offering clear insights into model performance across various experimental conditions.

7. Experimental Results and Analysis

7.1. Experiment 1: Analysis of the Proposed Model in This Study

Experiment 1 provides a comprehensive evaluation of the tripartite bargaining model proposed in this study for customized data product transactions, focusing on transaction success rates, price distribution, the relationship between final transaction prices and the remaining number of sellers, and the distribution of bargaining rounds.

Figure 8 presents the distribution of successful and failed transactions, with red points indicating successful transactions and blue points indicating failures. The horizontal and vertical axes represent the buyer and seller quotes, respectively, at the point where the transaction concludes (either successfully or unsuccessfully). The color gradient, from light to dark, denotes the remaining number of sellers at the end of the transaction, with darker colors indicating a higher number of remaining sellers. The overall transaction success rate is 92.70%, with a success rate of 97.87% within ten bargaining rounds. As the buyer's budget increases, the likelihood of a successful transaction rises, suggesting that higher budgets attract a greater number of sellers to participate in bidding.

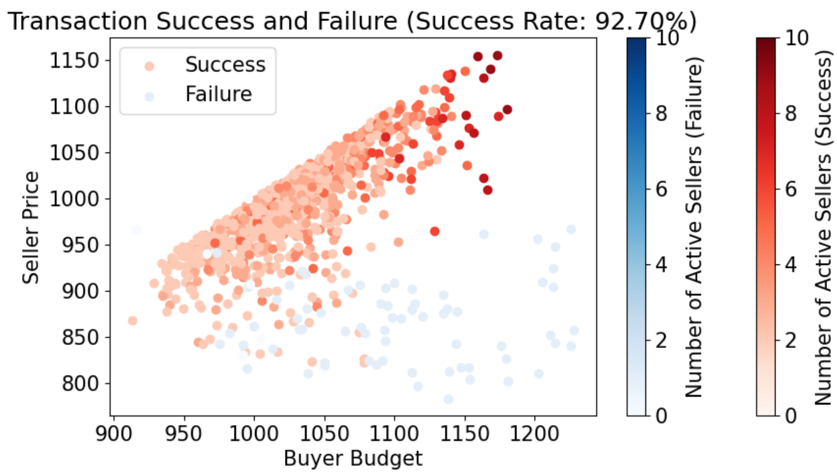

Figure 8. Starkberg–bargain game model: dot plot of successful and unsuccessful trades.

Figure 9 illustrates the distribution of optimal transaction prices, with the horizontal axis representing the optimal transaction price and the vertical axis indicating frequency. The transaction prices exhibit a normal distribution with a mean of 1000.73, closely aligning with the platform's reference price of 1000. This alignment highlights the model's effectiveness in guiding transaction prices toward the reference, thus promoting both market stability and fairness. The platform's reference price serves not only as directional guidance for transactions but also establishes a credible and authoritative price range for participants. Through its dynamic adjustment mechanism, the model further enhances stability, providing each party with a reliable pricing benchmark.

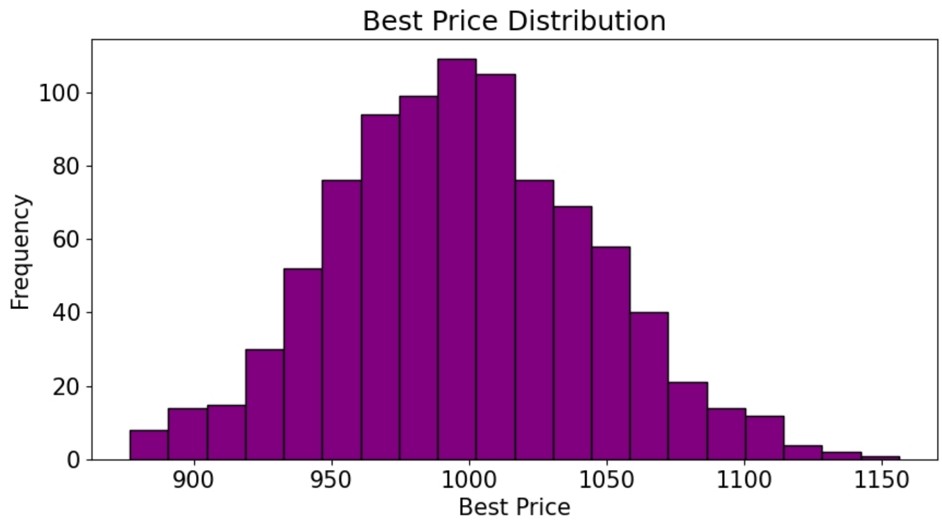

Figure 9. Stackberg–bargaining game model: best price histogram.

Figure 10 presents the relationship between the final transaction price and the remaining number of sellers, with the horizontal axis representing the number of remaining sellers upon successful transaction and the vertical axis indicating the optimal transaction price. The results indicate that when the number of sellers is 10, the median transaction price is relatively high and exhibits a concentrated distribution, reflecting price stability within a highly competitive environment. As the number of sellers decreases, the median price declines while price variability increases, allowing buyers to negotiate more advantageous transaction prices during the bargaining process. This outcome aligns with market competition dynamics, demonstrating that the model reasonably simulates the impact of competition on transaction prices.

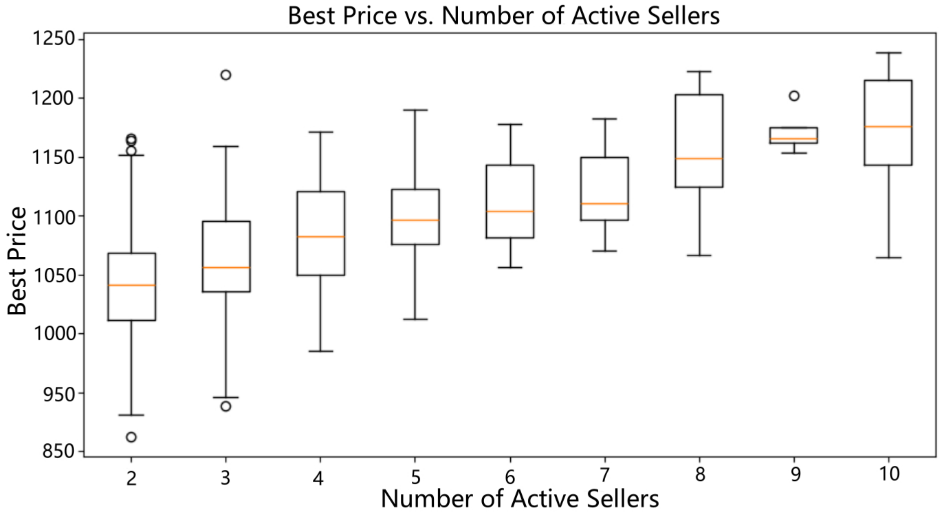

Figure 10. Stackberg–bargaining game model: A graph of the number of active merchants and the best price at the time a deal is reached.

Figure 11 illustrates the distribution of bargaining rounds required to conclude a transaction, with the horizontal axis representing the number of bargaining rounds at transaction completion and the vertical axis indicating frequency. The results demonstrate that most transactions are finalized within the initial rounds, particularly between the fourth and sixth rounds, suggesting that buyers and sellers frequently reach agreements through prompt price adjustments. Although a small proportion of transactions extend beyond the 10th round, such instances are uncommon, further underscoring the model's efficiency in managing complex transactions.

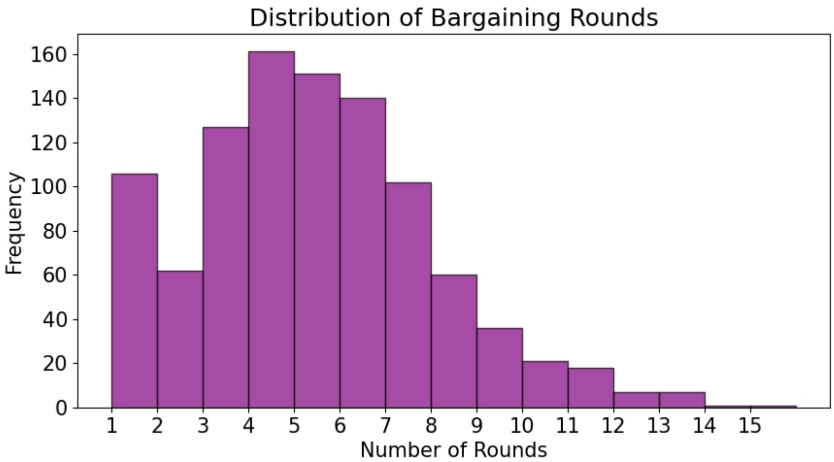

Figure 11. Starkberg–bargaining game model: game rounds histogram.

7.2. Experiment 2: Transaction Performance with Stackelberg Game Only

In Experiment 2, the transaction performance was analyzed under a scenario where only the Stackelberg game model was applied. As shown in Figure 12, the transaction success rate was 53.80%; significantly lower than that of the tripartite bargaining model. These results suggest that relying solely on the Stackelberg model is inadequate for effectively balancing the interests of buyers and sellers, leading to a higher transaction failure rate. In this scenario, only an initial reference price is provided by the platform, lacking both the bargaining process between the parties and the dynamic adjustment mechanism for the guidance price and price range, which substantially reduces model stability. Consequently, transactions are more likely to succeed only when buyer budgets and seller prices are closely aligned, while transactions with greater price discrepancies are more prone to failure.

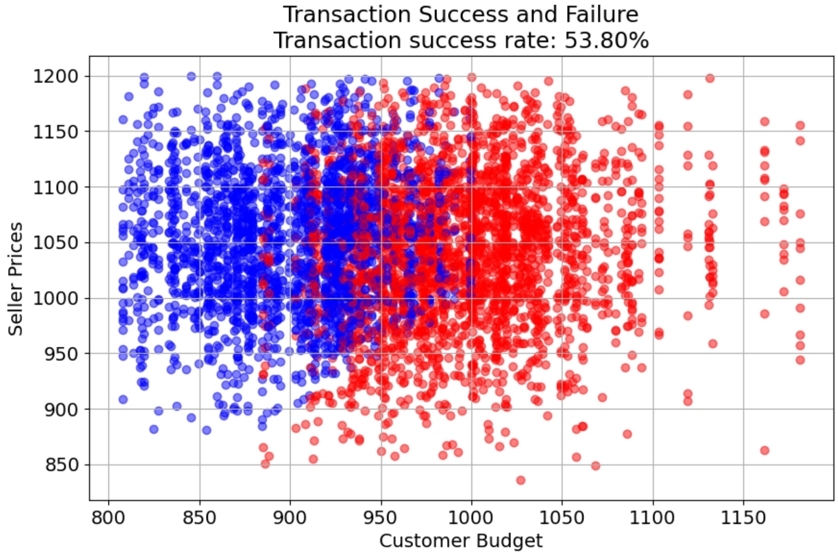

Figure 12. Only Starkerberg game model: dot plot of successful and unsuccessful trades.

Figure 13 illustrates the distribution of optimal prices, which is notably skewed compared to Experiment 1. The absence of dynamic bargaining adjustments resulted in transaction prices that do not adequately reflect market supply and demand.

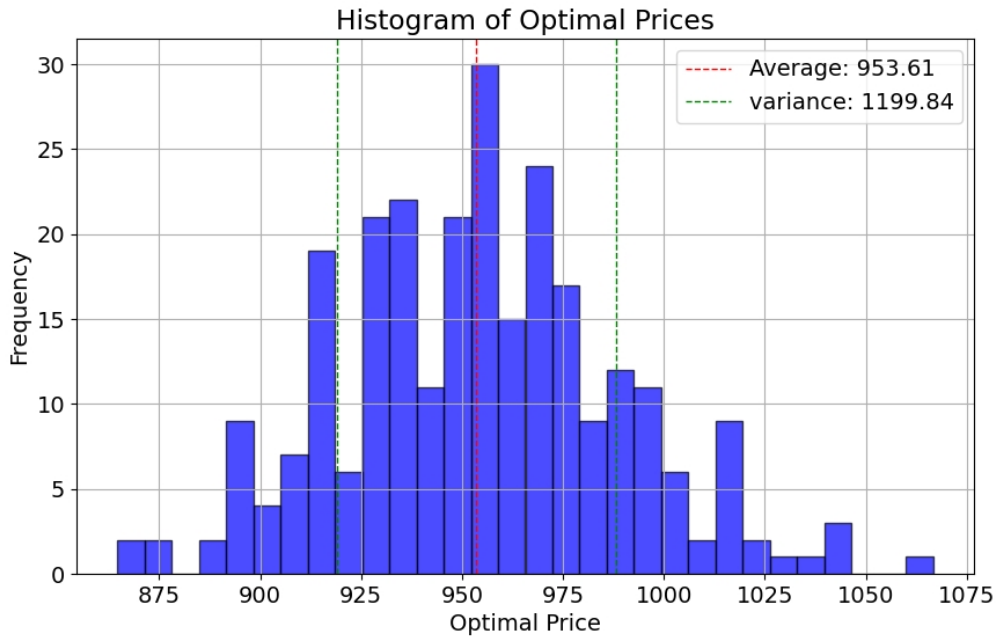

Figure 13. Only Starkerberg game model: best price histogram.

7.3. Experiment 3: Transaction Performance with Bargaining Game Only

Experiment 3 involved only the bargaining game model. Figure 14 shows a transaction success rate of 66.3%, with a success rate of only 39.4% within ten rounds of bargaining. Without platform-guided pricing, the bargaining process struggled to efficiently reach consensus, resulting in a high rate of failures.

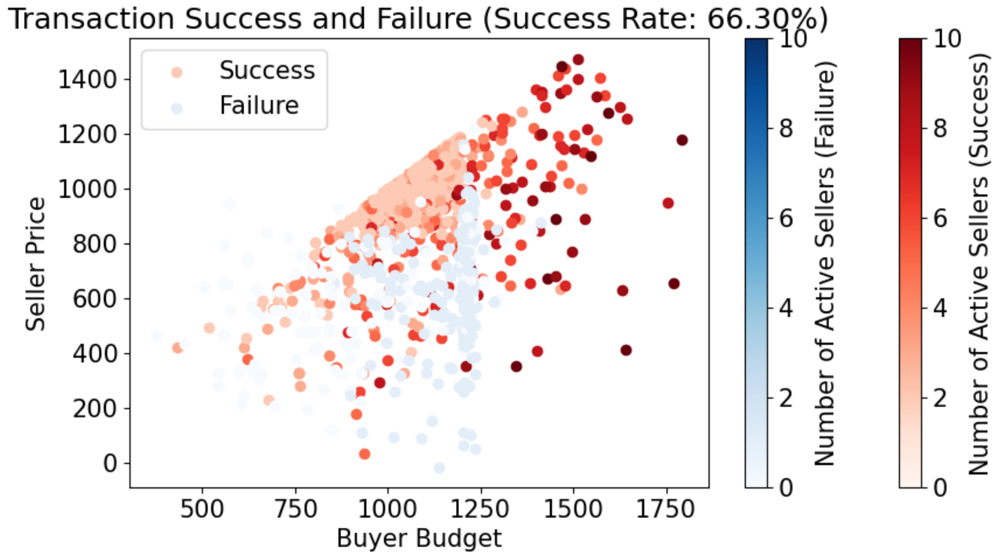

Figure 14. Only bargaining game model: dot plot of successful and unsuccessful trades.

In Figure 15, we illustrate the distribution of the optimal prices generated in Experiment 3, which involved only the bargaining game. It is evident that the prices are concentrated around the initial reference price, but the distribution is more dispersed and exhibits a noticeable right skew. Compared to the proposed three-party game model in this study, the price fluctuations in Experiment 3 are more pronounced, resulting in less stable transaction prices.

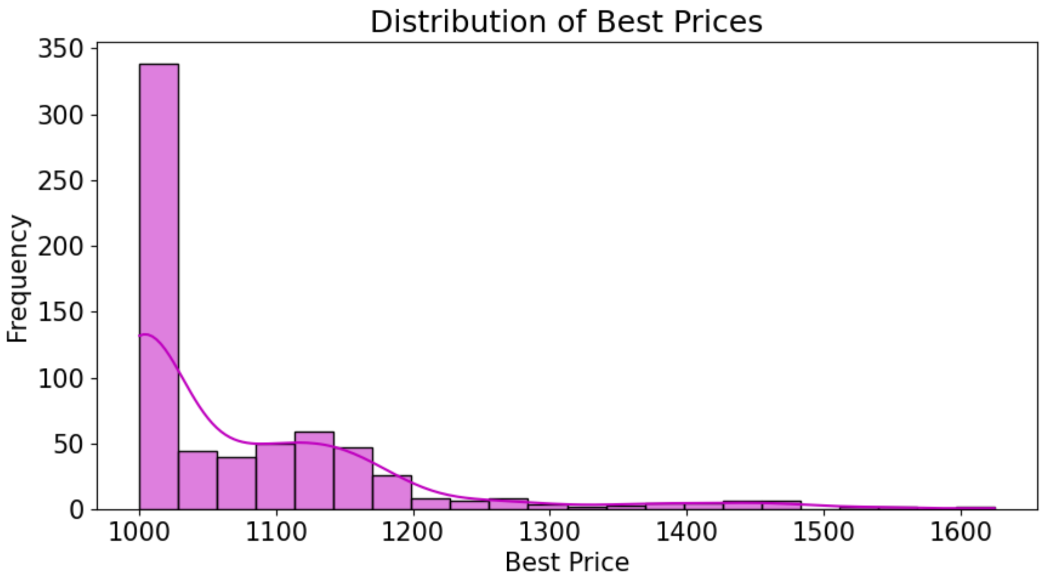

Figure 15. Only bargaining game model: best price histogram.

This phenomenon indicates that the model involving only the bargaining game lacks the platform's effective guidance in price determination, leading to significant uncertainty in price negotiations between buyers and sellers. Furthermore, the absence of platform participation in the game causes a loss of basis for adjusting the price range, thereby increasing the risk of transaction failure.

Overall, the experimental results highlight the superiority of the tripartite bargaining model, which integrates the strengths of the Stackelberg and bargaining games. This model improves transaction success rates and ensures price fairness and market stability.

7.4. Analysis of Transaction Success Rate

In this study, we conducted extensive experiments comparing the transaction success rates of the tripartite bargaining model and other classical bargaining models. The results indicate that the tripartite bargaining model exhibits a significant advantage in terms of transaction success rate. Specifically, the model achieved a success rate exceeding 80% across various experimental scenarios, which is considerably higher than that of traditional bilateral bargaining models. This advantage is primarily attributed to the tripartite model's ability to effectively integrate the interests of the buyer, seller, and platform, thus enabling the formulation of pricing strategies and dynamic adjustments that allow all parties to reach an optimal agreement, thereby enhancing the likelihood of a successful transaction.

7.5. Price Fairness and Reasonableness

In the assessment of price fairness, we employed various statistical methods to analyze the pricing outcomes of each model. The results demonstrate that the tripartite bargaining model performs robustly in terms of price fairness and reasonableness. First, the model exhibited minimal price volatility across multiple bargaining rounds, with the price distribution remaining relatively concentrated. This suggests that the model can generate reasonable prices without favoring any single party across different experimental scenarios. Furthermore, an analysis of the interests of all parties involved revealed that the tripartite bargaining model ensures that all parties receive fair benefits while avoiding excessive price bias, thereby contributing to the long-term stability of transactions.

7.6. Impact of Bargaining Efficiency and Dynamic Adjustment Mechanism

In our study of bargaining efficiency, we focused on the impact of the number of bargaining rounds and the dynamic adjustment mechanism on the bargaining outcomes. The experimental results show that as the number of bargaining rounds increases, both the transaction success rate and price fairness improve, although the efficiency of the bargaining process decreases. To address this, we introduced a dynamic adjustment mechanism, which significantly enhances bargaining efficiency by adjusting bargaining strategies and parameters. Specifically, the dynamic adjustment mechanism allows for the modification of bidding strategies and price ranges during the bargaining process based on the actual situation, thereby accelerating convergence, reducing unnecessary bargaining rounds, and ultimately achieving efficient and reasonable transaction outcomes.

7.7. Discussion

7.7.1. Unique Advantages and Enhancements of the Tripartite Model

The tripartite bargaining model presented in this study demonstrates unique advantages in data product pricing by accounting not only for the characteristics of data products but also for market conditions and trends. This model integrates the utility and benefits of buyers, sellers, and the platform, thereby dynamically aligning multi-party interests and accurately capturing the bargaining processes observed in real-world transactions.

Within this model, the platform continuously adjusts reference prices and price ranges, enabling real-time responses to changes in market demand and fluctuations. This mechanism allows the platform to manage buyer and seller expectations dynamically, effectively addressing market volatility and ensuring the stability, reliability, and fairness of the pricing mechanism. The model's multi-party coordination capabilities enhance its practical applicability, offering a more transparent and flexible market solution that effectively supports the pricing and transactions of customized data products.

7.7.2. Practical Application Scenarios of the Model

The tripartite pricing model proposed in this study, which integrates the Stackelberg model with bargaining games, demonstrates significant potential in the customized data products market. As industries like finance, healthcare, and marketing increasingly demand personalized data solutions, traditional pricing models often fall short in addressing these evolving needs. This model introduces a multi-party bargaining mechanism among the platform, buyers, and sellers, enhanced by an improved mean-variance utility function. This allows for a more precise alignment of interests, thus increasing transaction success rates and ensuring fair pricing.

In practical applications, the platform acts as a market coordinator, utilizing this model to provide reference prices and price ranges, enabling buyers and sellers to make more informed decisions during transactions. This mechanism not only enhances market transparency but also improves transaction flexibility and efficiency across diverse market conditions. However, challenges such as accurately defining and dynamically adjusting reference prices and balancing interests between buyers and sellers under varying market conditions remain. These issues underscore the need for further validation and refinement of the model for real-world applications.

7.7.3. Model Limitations and Improvement Directions

While the tripartite pricing model shows robustness in theoretical and experimental settings, it faces challenges in real-world applications due to the assumption of symmetric information. In practice, information asymmetry, particularly in data product transactions, can lead to inequitable outcomes between buyers and sellers. Moreover, the model simplifies the platform's role to that of a coordinator, overlooking potential influences from policies, regulations, and market competition. Future research should address these complexities, focusing on optimizing the bargaining process under conditions of asymmetric information and enhancing computational efficiency to improve the model's scalability in large-scale data transactions.

To further verify the robustness of the model, sensitivity analysis of parameters such as the initial reference price, risk aversion coefficients, and bargaining round limits should be conducted. Additionally, comparisons with findings from similar studies in the literature could emphasize the unique advantages or improvements of this tripartite model. Specifically, our model demonstrates higher transaction success rates due to its dynamic adjustment mechanism, which is not present in traditional bargaining models. The price distribution in our model is also more stable and aligned with the platform's reference price, addressing fairness concerns that are typically less emphasized in the existing literature. Furthermore, our model's efficiency in reducing the number of bargaining rounds to reach an agreement presents a significant improvement over other models where the bargaining process is less controlled. Lastly, the platform's active role in guiding pricing strategies in our model provides a more flexible and robust solution compared to models that treat the platform purely as a passive participant.

Future research could also explore potential regulatory and policy implications of the model, especially regarding market transparency and pricing fairness. To increase the model's relevance for real-world markets, further research is needed to examine its performance under asymmetric information and to investigate its scalability in handling larger numbers of buyers and sellers.

8. Conclusions

This study proposes a novel tripartite pricing model for customized data products, integrating platform, buyer, and seller dynamics within a game-theoretic framework. By combining Stackelberg and bargaining games, the model addresses key challenges in data product pricing, achieving improvements in transaction success rates, pricing fairness, and bargaining efficiency. Our experimental results demonstrate high success rates (92.70%) and bargaining efficiency with an average of 7.3 rounds to reach consensus. These outcomes validate the model's adaptability and efficacy across competitive, dynamic market conditions.

The model's contributions extend beyond traditional pricing frameworks by incorporating platform-guided bargaining processes that reduce uncertainties and align incentives for all parties. Specifically, it addresses the limitations of conventional Stackelberg and bilateral bargaining models by introducing a flexible price adjustment mechanism that adapts to real-time market fluctuations and competitive demands. This novel approach presents a valuable advancement in pricing mechanism design, offering enhanced theoretical insights and practical solutions for complex data trading scenarios.

Despite its strengths, certain limitations affect the model's applicability. The assumptions of symmetric information, fixed parameters, and the platform's simplified role may impact its generalizability to real-world scenarios. Additionally, computational complexity could limit its scalability for larger datasets, indicating the need for further testing across diverse market conditions. Future research should explore the model's robustness under asymmetric information settings and validate its scalability to accommodate larger data transactions. Testing in practical domains, such as smart manufacturing, the sharing economy, and fintech, could reveal its benefits in these fields, where data pricing faces unique challenges such as time-sensitive demand, privacy concerns, and competitive pressure.

Furthermore, the combined Stackelberg and bargaining game structure offers theoretical implications for pricing mechanisms by aligning decentralized bargaining with centralized guidance, promoting transparency and balanced incentives. Practical benefits include reduced negotiation time, improved alignment with stakeholder interests, and enhanced adaptability to market changes. As data platforms, buyers, and sellers navigate increasingly complex markets, this model provides an efficient, adaptable solution to support transparent and fair pricing strategies.

In conclusion, this tripartite pricing model demonstrates substantial advancements in pricing customized data products, laying a strong foundation for future studies to build upon and expand its application to broader market contexts.

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Appendix A

Algorithm A1 Bargaining Process for Customized Data Product Pricing

Require: Customized data product demand $X(x_1, x_2, x_3, ..., x_n)$, Buyer budget b, Initial guidance price p_o, Initial price range deviation d_o

Ensure: Optimal transaction price P^*, Final seller selection

1: **Step 1:** Buyer submits demand $X(x_1, x_2, x_3, ..., x_n)$ and budget b

2: **Step 2:** Platform sets initial guidance price p_o and price range $[p_o - d_o, p_o + d_o]$ based on demand complexity, market trends ω, and historical data

3: Initial price deviation:

$$d_o = k_1 \cdot \sigma_S + k_2 \cdot \sigma_B$$

where σ_S is the standard deviation of seller quotes, σ_B is the standard deviation of buyer budgets, and k_1, k_2 are dynamic adjustment factors.

4: **for** each bargaining round j **do**

5: **Step 3:** Sellers submit their quotes $o_{i,j}$ based on guidance price p_j and price range $[p_j - d_j, p_j + d_j]$

6: **Step 4:** Platform dynamically adjusts guidance price p_j and price range $[p_j - d_j, p_j + d_j]$ based on seller quotes $o_{i,j}$, buyer budget b_j, and market trends ω

$$p_{j+1} = \alpha_j \cdot M_B + (1 - \alpha_j) \cdot M_S$$

where M_B is the median of buyer budgets, M_S is the median of seller quotes, and α_j is the dynamic adjustment parameter.

The price range deviation is adjusted as:

$$d_{j+1} = k_1 \cdot \sigma_S + k_2 \cdot \sigma_B$$

Algorithm A1 *Cont.*

```
if U_j ≤ 0 or α_j ≤ 0 for buyer then
    Buyer exits the bargaining process
end if
for each seller i do
    if U_{i,j} ≤ 0 or β_{i,j} ≤ 0 for seller i then
        Seller i exits the bargaining process
    end if
end for
Step 5: If buyer exits or all sellers exit, bargaining ends, and the transaction fails
if At least one seller's quote o_{i,j} < b_j then
    Step 6: Bargaining ends, platform calculates optimal transaction price P* in range [o_{i,j}, b_j] to maximize platform utility
    Platform utility function:
```

$$u(p) = u(b)^{\alpha} \times u(o)^{\beta}$$

The optimal transaction price P^* is determined as:

$$P^* = \arg \max_{p \in [o_{i,j}, b_j]} \left(u(b)^{\alpha} \times u(o)^{\beta} \right)$$

```
    Platform sends P* to buyer and sellers
  end if
end for
Step 7: Sellers send acceptance/rejection of P* to the platform
Step 8: Platform selects final seller based on historical records, seller market competitiveness, etc.
Step 9: Transaction succeeds with selected seller at price P*
Platform Guidance Price Adjustment Mechanism:
Guidance price adjustment:
```

$$P_{t+1} = \alpha \cdot M_B + (1 - \alpha) \cdot M_S$$

Guidance price range adjustment:

$$R_{t+1} = [P_t - k_1 \cdot \sigma_S - k_2 \cdot \sigma_B, P_t + k_1 \cdot \sigma_S + k_2 \cdot \sigma_B]$$

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