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Optimization Algorithm of Internet Many-to-Many Data Transactions Based on Auction Theory

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Abstract: With the continuous growth in demand for multilateral data exchange on the Internet, traditional data transaction mechanisms are encountering bottlenecks in efficiency, fair pricing, and privacy protection, making it difficult to meet the collaborative optimization needs in a multi-participant environment. Therefore, a many-to-many data transaction optimization algorithm driven by auctions is proposed. This approach aims to maximize social welfare, incorporates privacy discount factors and stability screening mechanisms to create a utility regulation model, and introduces transaction price regulation strategies to handle heterogeneous bidding behaviors. Finally, efficient pairing is achieved through Lagrange relaxation and heuristic search. In low, medium, and high privacy level scenarios, the incentive imbalance indices of the proposed algorithm were 0.016, 0.017, and 0.021, respectively. The price deviation indices for the three types of bid asymmetry scenarios were 0.048, 0.052, and 0.060, respectively. The engagement rates of high-privacy users were 0.920, 0.909, and 0.870, respectively. The experimental results demonstrate that the proposed algorithm maintains stable matching efficiency, fair pricing, and strong incentive response across different privacy preferences and bidding structures, providing effective technical support for optimizing the design of multilateral data transaction mechanisms and platform systems construction.

Keywords: Auction theory, data trading, privacy optimization, heuristic algorithms, internet transactions.

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1. Introduction

As data resources become increasingly important for Internet platforms, how to enable efficient data circulation while ensuring privacy, security, and fair transactions has become a key issue for governance in the information society and the development of the digital economy (Hsieh, 2024; Williams, 2023). The traditional transaction model, which relies on centralized platforms for matchmaking, faces serious challenges related to participant diversity, resource matching efficiency, and mechanism interpretability. Especially in many-to-many transaction environments, factors such as pricing power distribution, bidding strategies, and privacy concerns are tightly linked, further increasing the complexity of modeling and optimizing transaction systems (Addya et al., 2021; Huang and Li, 2024). In recent years, the integration and application of technologies like blockchain, game theory, and smart contracts have offered new ideas for establishing secure and trustworthy data transaction mechanisms, leading to the development of some data transaction models designed for multiple participants with dynamic game structures (Zhang et al., 2023).

In this context, many scholars have conducted extensive research on resource transaction security, multi-party incentive design, and social welfare optimization goals. Luo et al. (2021) proposed a blockchain-based bidirectional electricity transaction architecture for vehicle-to-vehicle and vehicle-to-grid systems, addressing the lack of information sharing and privacy protection mechanisms in electric vehicle energy transactions. They designed a pricing mechanism that combined Bayesian game theory with bidirectional auctions. The simulation results showed that this method improved social welfare and cost control by 102.8% and 319%, respectively. Due to the scarcity of spectrum resources and transaction security issues in the multiple Unmanned Aerial Vehicles (multi-UAV) edge computing system, Xu et al. (2024) combined blockchain resource transaction mechanisms with two-way auction theory and designed a pricing-based incentive strategy through a two-stage game. The security assessment and numerical results verified the effectiveness of this mechanism in utility optimization and fairness. Wang et al. (2023) proposed a social welfare maximization bilateral auction mechanism with price discrimination to address the efficiency gap and privacy protection issues in the electricity and heating markets. They constructed a distributed bidding algorithm to achieve supply-demand balance. The experimental results showed that the mechanism improved social welfare by 4% to 15%, while also verifying the distributed feasibility of the algorithm. Luong et al. (2024) introduced a multi-unit auction model based on deep learning and the Myerson mechanism, incorporating semantic communication to reduce data offloading costs. Their research combined computational valuation and communication characteristics for training optimization. The results demonstrated that the proposed mechanism outperformed traditional mechanisms in incentive compatibility, budget constraints, and resistance to false bidding.

With the widespread use of artificial intelligence, evolutionary computing, and data-driven methods in financial transactions, many researchers have conducted in-depth studies on online investment optimization, trend prediction, and strategy development. He and Peng (2023) proposed an adaptive moment estimation strategy to solve the problem that existing online investment strategies struggle to balance the efficient use of historical data with quick execution. This method processed data incrementally, combining linear time complexity with strategy robustness. Experimental results showed that this approach performed very well in terms of performance metrics and transaction cost tolerance. Giorgi et al. (2024) focused on creating effective trading strategies while considering transaction costs and asset dynamics, and proposed a reinforcement learning algorithm. In an ideal scenario, this algorithm could approximate the optimal strategy. In more complex nonlinear market conditions, reinforcement learning proved to be a practical alternative to traditional theoretical strategies. Chen et al. (2021) introduced a stock price trend prediction method that integrated keyword extraction and signal confirmation to address the integration of financial news and technical indicators. They developed an improved model based on a genetic algorithm. The results indicated that this optimization method outperformed others when tested on real data. Adegboye et al. (2023) proposed a multi-strategy optimization framework that combined directional change theory and genetic algorithms to overcome the limitations of traditional physical time trading strategies. This method identified trend reversal signals using a classification regression model and outperformed several benchmark strategies in empirical foreign exchange market analysis.

In summary, although many existing many-to-many data trading mechanisms have made notable progress in game-theoretic modeling, double-auction pricing, and resource allocation optimization, several limitations remain. First, most auction-based models focus on unilateral or bilateral trading structures and thus fail to capture heterogeneous bidding behaviors in large multi-agent environments. Second, blockchain-enabled or privacy-aware auction schemes commonly rely on homogeneous privacy assumptions and do not adequately address the dynamic trade-off between privacy protection and allocation efficiency. Third, many prior multi-agent auction mechanisms depend on centralized or scale-limited matching procedures, which constrain stability and extensibility in large-scale markets. Consequently, there is still considerable room for improvement regarding matching stability, system scalability, and fairness under privacy constraints.

To address these gaps, this study proposes the Auction-driven Optimization Algorithm for Many-to-Many Data Trading (AOMDT), designed to enhance market coordination, incentive compatibility, and trading efficiency in multi-agent settings. The AOMDT framework consists of three core components: a social–welfare–maximizing utility model, a dynamic pricing mechanism integrating trust and stability considerations, and a multi-sided optimal matching algorithm based on Lagrangian relaxation and heuristic search.

The contributions of this study are threefold. First, a privacy-discount factor and stability-filtering mechanism are introduced to provide robustness under diverse privacy preferences and strategic bidding behaviors. Second, a transaction-adjustment strategy is designed to accommodate asymmetric bidding, thereby improving pricing consistency and incentive compatibility. Third, a scalable multi-sided bidding optimization process is developed, where hierarchical solving and heuristic matching enhance system adaptability and computational efficiency in large-scale market scenarios. This mechanism aims to complement existing auction theory and research on multi-entity data markets in both theory and application.

2. Methods and Materials

2.1. Design of One-To-Many Data Transaction Algorithm

The study begins with a one-to-many structure to analyze policy stability and incentive constraints under unilateral dominance through contract design, providing an analytical basis for expanding complex interactive structures in the future. In practical data transaction scenarios, it is common for a single data provider (seller) to sell data resources to multiple demanders (buyers), especially on open data platforms and online service platforms where enterprise users gather and trade individual user data centrally. Therefore, the study introduces contract theory as the modeling foundation to analyze how sellers can incentivize buyers to truthfully report their preferences through optimal contract design when dealing with multiple heterogeneous buyers, ultimately improving overall transaction utility. First, the evolution model of transaction mechanisms driven by contractual relationships is illustrated in Fig. 1 (Curiel-Cabral et al., 2024).

As shown in Fig. 1, the mechanism illustrates how buyers dynamically decide to participate based on their satisfaction with the transaction contract. Satisfaction leads to continued cooperation, while dissatisfaction results in withdrawal. The process involves three key interaction dimensions: interest, power, and control, which jointly shape contract execution and overall transaction performance (Ji et al., 2022). To better clarify the focus of the research, Fig. 2 provides a schematic diagram of a one-to-many data transaction structure.

In Fig. 2, the seller designs multiple heterogeneous contracts (Contract 1 – Contract n) targeting different buyer types. Buyers autonomously select whether to participate based on their private valuation and perceived utility, forming a screening process driven by asymmetric information. The diagram highlights the core interaction flow in one-to-many data trading:

the seller broadcasts contract options, buyers evaluate and respond according to their type parameters, and the resulting selections determine the transaction outcomes and the overall efficiency of the mechanism. (Zhou et al., 2024).

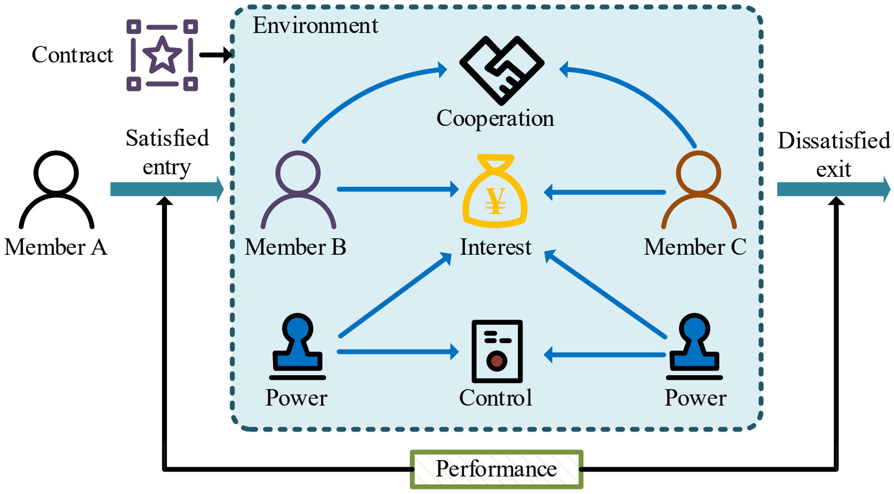


Fig. 1. Evolution model of transaction mechanism driven by contractual relationship

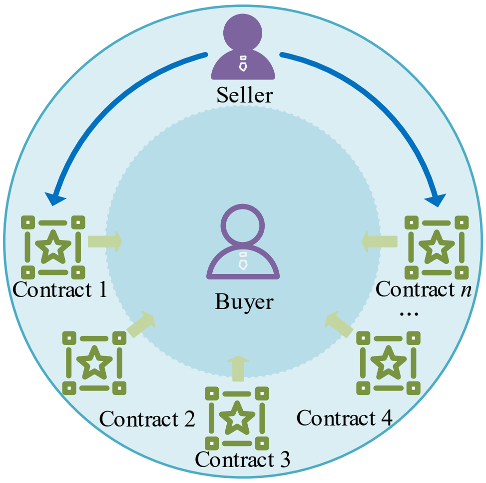


Fig. 2. One-to-many data transaction structure

Assuming that there is a data seller S and n potential data buyers $\{B_1, B_2, ..., B_n\}$, each buyer B_i has a private type parameter $\theta_i \in [\underline{\theta}, \overline{\theta}]$ representing their valuation level or data utilization efficiency. This type of information is only known to the buyer themselves, forming a typical information asymmetry structure.

The seller designs a set of contracts $C(\theta) = \{q(\theta), t(\theta)\}$ for each possible θ_i, where $q(\theta)$ represents the data quality provided to the buyer of type θ and $t(\theta)$ is the transaction price they need to pay. The utility function of the buyer is defined in Eq. (1).

$$U_i(\theta_i) = \theta_i q(\theta_i) - t(\theta_i) \tag{1}$$

In Eq. (1), $U_i(\theta_i)$ represents the utility of buyer i, which is the price minus the profit. The seller is unable to observe θ_i and needs to design a set of contracts that meet the constraints of Incentive Compatibility (IC) and Individual Rationality (IR) to guide the buyer to choose contract items that match their true type. The seller's goal is to maximize their own profit function, as shown in Eq. (2).

$$\Pi = \int_{\underline{\theta}}^{\overline{\theta}} [t(\theta) - c(q(\theta))] f(\theta) d\theta \tag{2}$$

In Eq. (2), $f(\theta)$ is the probability density function of the buyer type. $c(q)$ is the cost function provided by the seller to the buyer when the data quality is q. Assuming it is a strictly convex function, it often takes the form $c(q) = \frac{1}{2} kq^2$, where

$k > 0$ represents the unit data quality cost coefficient. To ensure that the buyer chooses the contract according to its true type, the following two conditions need to be met. Eq. (3) displays the IC condition.

$$\theta q(\theta) - t(\theta) \geq \theta q(\hat{\theta}) - t(\hat{\theta}), \quad \forall \hat{\theta} \neq \theta \tag{3}$$

Eq. (3) states that for any alternative type $\hat{\theta}$, the utility obtained by the buyer θ from choosing a contract that matches its own type should not be lower than choosing other contracts. The second IR condition is shown in Eq. (4).

$$\theta q(\theta) - t(\theta) \geq 0 \tag{4}$$

Eq. (4) ensures that participants will not receive negative utility after choosing a contract, thereby ensuring participation in the transaction. The Myerson simplification method transforms constraints into monotonicity and boundary condition forms. The original problem can be reconstructed into a standard optimization problem. If $v(\theta) = \theta q(\theta) - t(\theta)$ is the indirect utility function of the buyer, it can be deduced that the optimal contract structure should satisfy Eq. (5).

$$\frac{dv(\theta)}{d\theta} = q(\theta), \quad v(\underline{\theta}) = 0 \tag{5}$$

In Eq. (5), $\underline{\theta}$ represents the lower bound of the buyer type parameter. $t(\theta)$ is expressed as Eq. (6).

$$t(\theta) = \theta q() - \int_{\underline{\theta}}^{\theta} q(s)ds \tag{6}$$

Subsequently, it is substituted into the seller's objective function to obtain the final optimization problem form, as shown in Eq. (7).

$$\max_{q(\theta)} \int_{\underline{\theta}}^{\bar{\theta}} \left[\theta q(\theta) - \int_{\underline{\theta}}^{\theta} q(s)ds - c(q(\theta)) \right] f(\theta) d\theta \tag{7}$$

Eq. (7) is a function extremum problem with an integral nested structure. The study introduces Lagrange multipliers based on the variational method to construct optimal solution conditions and introduces an optimization strategy combining gradient descent and the quasi-Newton method in numerical experiments to improve solving efficiency and convergence stability. Therefore, the flow of the one-to-many data transaction algorithm is shown in Fig. 3.

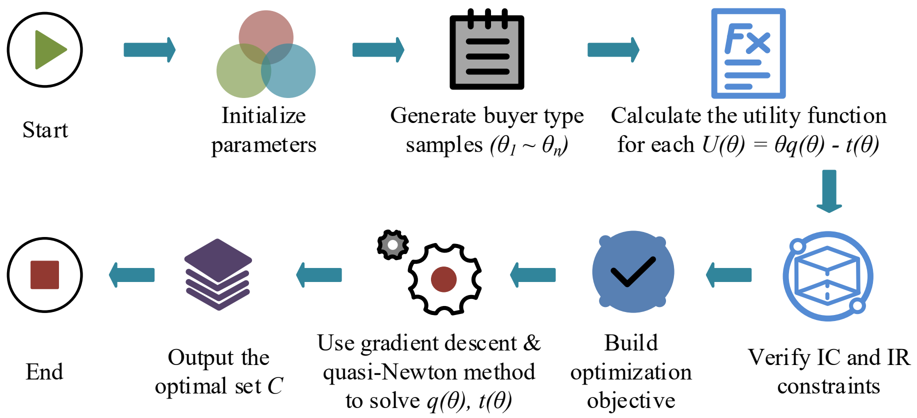


Fig. 3. One-to-many data transaction algorithm process

As shown in Fig. 3, first, the buyer type space is initialized and sampled to create a participant set that reflects the actual market distribution. Next, based on the initial contract structure set by the seller, the utility functions of each buyer type under different contracts are calculated, and each is verified for incentive compatibility and individual rationality constraints. Building on these constraints, the algorithm constructs an expected return objective function and introduces a hybrid optimization strategy combining gradient descent and quasi-Newton methods to iteratively solve for data quality and pricing strategies, ultimately producing the optimal contract set.

2.2. Optimization Algorithm for Many-To-Many Data Transactions based on Auction Theory

The one-to-many mechanism used in the previous section as a structural simplification model helps clarify individual motivation logic and preference expression. Building on this, a bidirectional auction framework is further introduced to extend to many-to-many scenarios and achieve a systematic transition from a unilateral game to bilateral matching. By incorporating a neutral third-party platform to coordinate bidding and acceptance rules among various bidders and sellers, and including privacy leakage cost factors, market efficiency can be maximized while ensuring transaction fairness. Fig. 4 illustrates the structure of many-to-many data transactions.

Fig. 4 illustrates the basic interaction framework of the many-to-many data transaction environment. Multiple bidders submit their heterogeneous bidding information to the third-party platform, while sellers simultaneously publish transaction conditions. The platform aggregates these inputs and forms the initial candidate matching space, providing the structural foundation for subsequent optimization. Furthermore, Fig. 5 shows a systematic schematic diagram of the many-to-many data transaction mechanism.

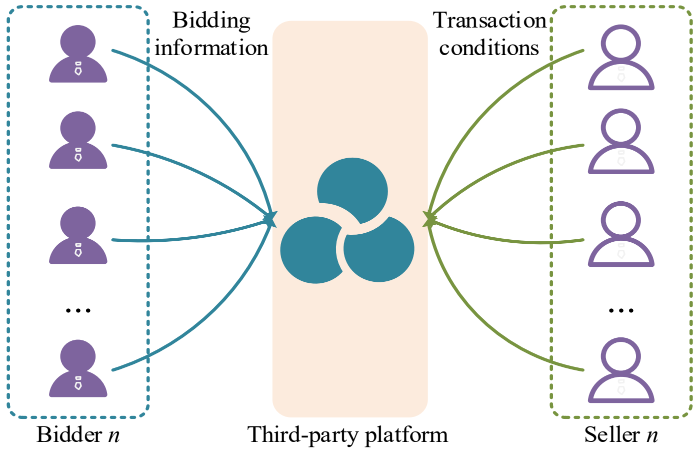


Fig. 4 Schematic diagram of many-to-many data transaction structure

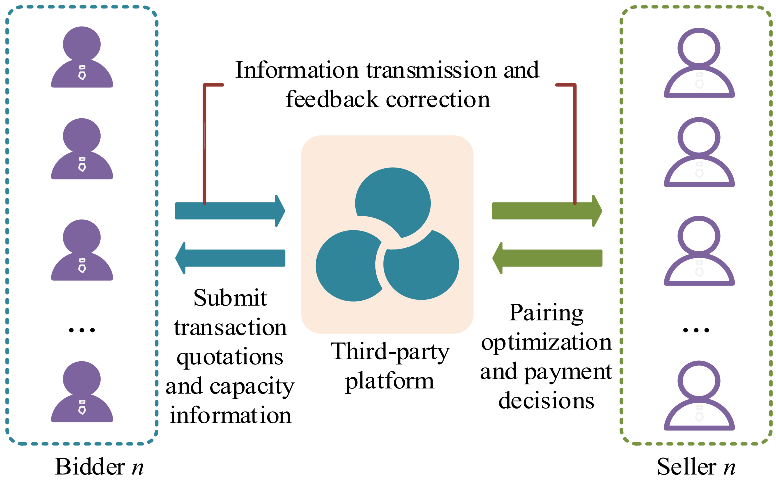


Fig. 5 Auction-driven many-to-many data transaction mechanism diagram

As shown in Fig. 5, the entire mechanism consists of two key steps. First, the buyer and seller submit transaction quotes and capacity information through the platform. The second is that the platform optimizes pairing and makes payment decisions based on auction rules. The bidirectional arrows in the figure represent the information transmission and feedback correction during the bidding process, reflecting the strategic dynamism and game interaction in the auction mechanism (Kong et al., 2023; Baldwin et al., 2024).

To establish a many-to-many data transaction optimization model, a multilateral transaction system with the goal of maximizing social welfare is constructed based on the bidirectional auction mechanism. The system consists of M auctioneers (sellers) and N bidders (buyers), represented as sets $S=\{s_1,s_2,\ldots,s_M\}$ and $B=\{b_1,b_2,\ldots,b_N\}$, respectively. Each seller s_i has a tradable data resource and sets its minimum acceptance price a_i. Each buyer b_j has a maximum bid limit β_j for the required data. Both bids are submitted through a third-party platform to form a bid set.

The transaction matching relationship is established through a binary variable matrix $X=\left[x_{ij}\right]\in\{0,1\}^{M\times N}$, where $x_{ij}=1$ represents the transaction between seller s_i and buyer b_j. Conversely, $x_{ij}=0$. Meanwhile, the transaction price matrix $P=\left[p_{ij}\right]$ is introduced to represent the transaction price determined by the platform when $x_{ij}=1$, which needs to satisfy Eq. (8).

$$a_i \le p_{ij} \le \beta_i\,,\quad for\quad x_{ij}=1 \tag{8}$$

In Eq. (8), x_{ij} is the indicator variable for whether the buyer and seller have completed the transaction. To ensure participation constraints, each buyer and seller is only allowed to match with one party in a transaction cycle, resulting in the following pairing constraints, as shown in Eq. (9).

$$\begin{aligned} &\sum_{j=1}^{N} x_{ij} \le 1, \quad \forall i = 1,\ldots,M \\ &\sum_{i=1}^{N} x_{ij} \le 1, \quad \forall j = 1,\ldots,N \end{aligned} \tag{9}$$

To satisfy the above matching constraints, the platform needs to select the combination that maximizes the system utility among all feasible pairings (Ena et al., 2022). The study takes the social welfare system as the optimization objective, where the buyer's return is $\beta_j - p_{ij}$, and the seller's return is $p_{ij} - a_i$. The overall transaction utility is expressed as Eq. (10).

$$W = \sum_{i=1}^{M} \sum_{j=1}^{N} x_{ij} (\beta_j - a_i) \tag{10}$$

In Eq. (10), W represents the overall transaction utility. However, in actual data transactions, data resources often come with privacy breaches or differences in processing costs (Zhao and Xu, 2022). To this end, a privacy-sensitive discount factor $\lambda_{ij} \in (0,1]$ is introduced, which reflects the trust weight or utility attenuation degree of users or platforms under privacy/security constraints in the $s_i \to b_j$-path. The final social welfare function is updated to Eq. (11).

$$W' = \sum_{i=1}^{M} \sum_{j=1}^{N} x_{ij} \lambda_{ij} (\beta_j - a_i) \tag{11}$$

In addition, the platform needs to determine the actual transaction price p_{ij}. Based on the improved McAfee mechanism, a mediation transaction price is set among all valid pairings, and its expression is shown in Eq. (12).

$$p_{ij} = \frac{a_i + \beta_i}{2} - \gamma_{ij} \tag{12}$$

In Eq. (12), $\gamma_{ij} \ge 0$ is the platform regulatory factor (which can be used to guide incentives or offset taxes). If p_{ij} falls outside the acceptable range, it is considered a mismatch (x_{ij} =0). To avoid irrational bidding behavior, the platform introduces a quotation stability index, as shown in Eq. (13).

$$\delta_{ij} = \frac{|\beta_i - a_i|}{\beta_i + a_i} \tag{13}$$

In Eq. (13), if the stability index δ_{ij} of the quotation is less than the set threshold ϵ, it indicates that the quotation range is too narrow or the fluctuation is insufficient, which may be an invalid match. The platform can choose to reject the transaction or lower its pairing priority. Finally, by combining the above variable definitions, constraints, and objective functions, the platform can transform the many-to-many transaction matching problem into a weighted bipartite graph maximum matching problem, which can be solved by combining Lagrangian relaxation and heuristic search.

In practical deployment, to improve the execution efficiency and system stability of the algorithm, modules such as price pruning, privacy trust regulation, and matching stability filtering are introduced to construct a complete auction-driven many-to-many data transaction process. Fig.6 shows the execution steps of the AOMDT algorithm.

As shown in Fig. 6, AOMDT starts with initializing the set of participants and key parameters. The platform first collects the bidding and privacy trust information of both buyers and sellers, and constructs a candidate transaction matrix. Subsequently, by calculating the stability index δ_{ij} for each pair, pruning is performed on pairs that do not meet the threshold requirements to screen out inefficient or manipulative risk transaction pairs from the source. On this basis, the platform calculates the transaction price p_{ij} for each feasible pairing and constructs a weighted matching graph based on the privacy discount factor λ_{ij}. Finally, the maximum weighted matching algorithm is used to solve the optimal pairing scheme and output the corresponding final payment result.

3. Results

3.1. AOMDT Algorithm Basic Performance Testing

The entire experiment is conducted in the Python 3.10 environment, primarily using an Intel Core i7-12700H CPU, 16GB of memory, and Windows 11, with single-threaded execution to ensure a fair comparison of different algorithms. The dataset includes synthesized iData-Trans simulated bidding data and real University of California, Irvine (UCI) Online Auctions data. The former contains about 2,000 virtual buyer-seller transaction records, covering fields such as participant number, bidding range (starting price/highest price), privacy-sensitive factors, matching labels, and more. The latter comes from real online auction platforms like eBay, featuring 627 auction processes and behavioral data from 481 bidders. Fields include auction item types, starting prices, bidding records, transaction prices, and auction timestamps. First, a joint sensitivity analysis experiment is performed on key parameters. The results are shown in Table 1.

As shown in Table 1, when λ was set to 0.3 and ϵ was set to 0.08, the system's Social Welfare (SW) reached its highest value of 105.30. However, at this point, the Valid Match Rate (VMR) dropped to 0.7665. This indicates that although high privacy tolerance and loose screening can increase total returns, they can lead to a decrease in matching quality. On the contrary, when λ=0.5 and ϵ=0.02, the highest VMR was 0.8900, but the SW was only 92.74, showing a certain trade-off trend between benefits and quality. Overall, the increase λ leads to conservative quotes from participants, thereby lowering the overall matching returns. Although increasing ϵ can relax screening, it is also prone to introducing low-quality pairings. Taking into account the balance between system robustness and performance, the subsequent experiments will uniformly adopt a parameter combination of λ=0.5 and ϵ=0.06.

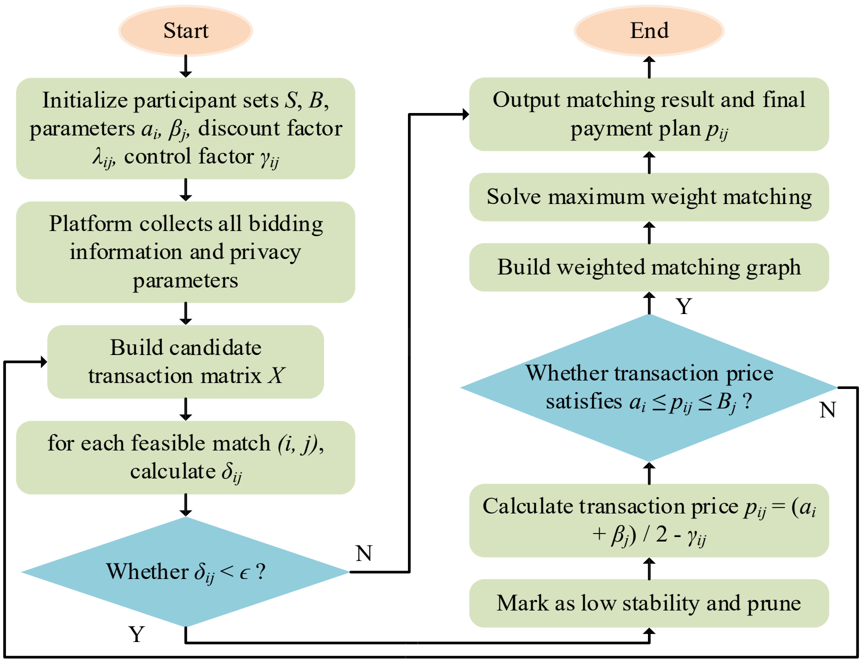


Fig. 6. Auction-driven optimization algorithm for many-to-many data transaction flow chart

To verify the contribution of each key mechanism to the overall performance of the algorithm, four model configurations are set up for comparative analysis. The complete model AOMDT includes a privacy regulation mechanism λ, a transaction stability screening mechanism ϵ, and a price regulation mechanism γ. AOMDT-λ represents removing the privacy discount mechanism, which is uniformly set to 1 and ignores the privacy preferences of participants. AOMDT-ϵ means to cancel the screening process for stability indicators, and all pairs are not constrained by the ϵ-threshold; AOMDT-γ means no longer using the regulatory factor γ, and the transaction price is directly set as the average buying and selling price. The experimental results are shown in Fig. 7.

In Fig. 7(a), AOMDT maintained the lowest Transaction Fairness Index (TFI) throughout the iteration process and showed a stable downward trend. After introducing privacy control, stability screening, and transaction control mechanisms, the system could effectively guide the convergence of buying and selling strategies and continuously optimize the utility allocation structure. The TFI of AOMDT-λ was higher than other models, indicating that ignoring user privacy sensitivity could lead participants to adopt more aggressive or uncooperative bidding strategies, ultimately disrupting utility balance. The overall fairness and stability of AOMDT-ϵ was poor, indicating that the transaction stability screening mechanism played an important role in optimizing the system structure. The AOMDT-γ curve was at an intermediate level, indicating that although the transaction price regulation mechanism was not a decisive factor in fairness, it still had auxiliary value in regulating resource allocation structure. In Fig. 7(b), the Average Platform Revenue (APR) curve of AOMDT remained at the highest level and gradually converged in the later stages of iteration, indicating that the transaction price regulation in the auction mechanism could effectively enhance the platform's profitability as an intermediary.

To evaluate the execution efficiency and matching stability of AOMDT in different market sizes, five sets of symmetric transaction scenarios are set up, namely S1 (100 buyers and 100 sellers each), S2 (200 sellers each), S3 (400 sellers each), S4 (600 sellers each), and S5 (800 sellers each). Under other fixed parameter conditions, the performance of each method in response time and pairing stability is tested. The comparative methods include Focal Loss-based Auction Mechanism (FLAM), Bayesian Double Auction (BDA), and Privacy-aware McAfee Auction (PMAA), all of which are typical multilateral auction modeling frameworks. The results are shown in Fig. 8.

Response time and pairing stability not only reflect the computational efficiency of the algorithm but also the effectiveness of market resource allocation: shorter response time means that the platform can still complete transactions promptly under high concurrency conditions, while higher pairing stability means a lower probability of renegotiation, which can reduce transaction costs for participants and improve overall market efficiency and user experience. In Fig. 8(a), when the market size reached S5, the average response times of AOMDT, FLAM, BDA, and PMAA were 12.4, 14.2, 13.8, and 13.0, respectively. In Fig. 8(b), the corresponding pairing stability rates were 0.85, 0.80, 0.82, and 0.83, respectively. AOMDT maintained excellent response speed and matching stability when handling large-scale transactions. The introduced stability screening mechanism and transaction price regulation module effectively compress irrational transaction paths and reduce the probability of inefficient pairing. In contrast, FLAM focuses more on maximizing individual utility in deep incentive mechanisms, resulting in processing delays under resource scarcity conditions. Although PMAA has certain privacy protection advantages, its matching efficiency slightly decreases in the absence of a price adjustment mechanism. BDA introduces more intermediate calculation steps in the negotiation game strategy, which increases the system load.

Table 1. Results of the joint sensitivity analysis experiment

λ (Privacy Discount)	ò (Stability Threshold)	Social Welfare (SW)	Valid Match Rate (VMR)
0.3	0.02	99.08	0.8873
0.3	0.04	98.97	0.8601
0.3	0.06	100.52	0.8200
0.3	0.08	105.30	0.7665
0.5	0.02	92.74	0.8900
0.5	0.04	92.65	0.8463
0.5	0.06	98.11	0.8094
0.5	0.08	99.81	0.7615
0.7	0.02	86.81	0.8772
0.7	0.04	89.45	0.8247
0.7	0.06	95.40	0.8055
0.7	0.08	94.53	0.7883
0.9	0.02	80.61	0.8535
0.9	0.04	83.09	0.8091
0.9	0.06	89.20	0.7918
0.9	0.08	88.81	0.7707

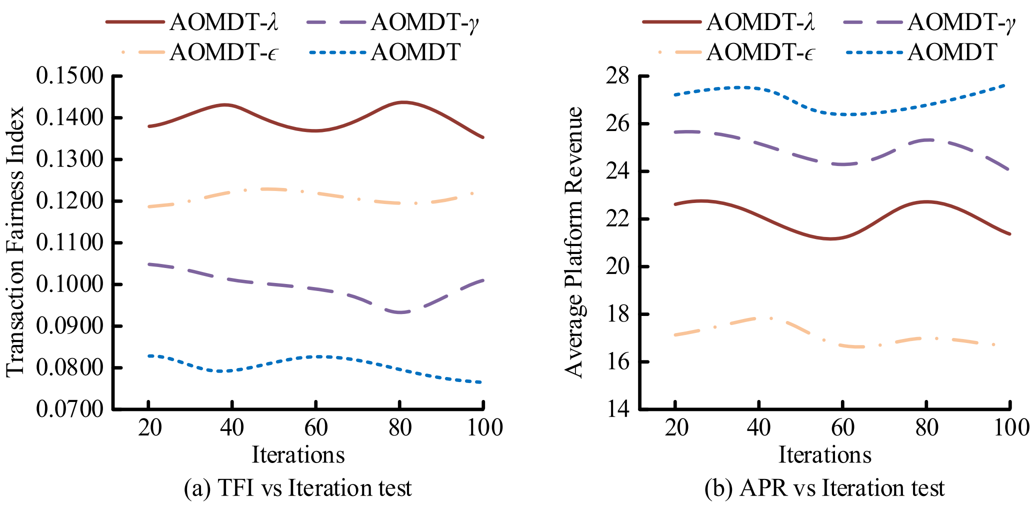
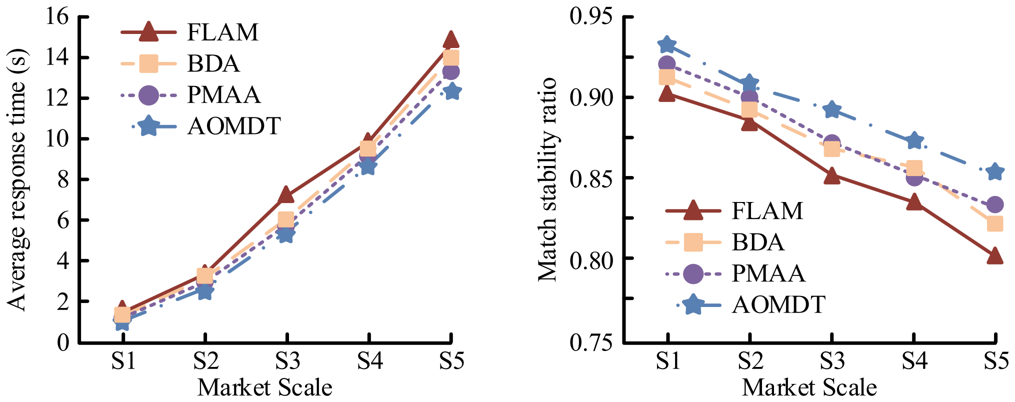


Fig. 7. Mechanism module ablation test results

3.2. Practical Application Testing of the AOMDT Algorithm

To ensure that the practical evaluation reflects real market conditions, this section is conducted using the UCI Online Auctions dataset, which contains authentic bidding behaviors from real auction platforms such as eBay. The comparative method introduces three key algorithms with adaptive regulation or content-driven capabilities: Self-Adaptive Double Auction Mechanism (SADAM), Hybrid Incentive Matching Auction (HIMA), and Content-Aware Game-based Matching Mechanism (CAGMM), to develop a more comprehensive multi-model comparison system. In many-to-many data transaction systems, participants usually adjust their bidding strategies dynamically based on previous game results. Therefore, a multi-round bidding game environment is established to verify the system's steady-state behavior and actual functionality. The results are shown in Table. 2.



(a) Average response time test (b) Match Stability Ratio test

Fig. 8. Execution efficiency and matching stability test under different market sizes

Among the indicators, social welfare directly measures the total utility of both parties in a transaction and is a core indicator of resource allocation efficiency; the matching rate reflects the market's ability to achieve effective transactions; and ABR reflects the stability of participant's behavior, with lower volatility implying higher strategy predictability and lower learning costs. In Table 2, AOMDT achieved the highest social welfare of 105.3 in a convergent stable state, with a match rate of 0.85 and an average computation time of 1.43 seconds. In contrast, FLAM's social welfare was only 98.7, and the average bid change was 0.058, indicating its strategy oscillation issue in multi-round games. Although FLAM and HIMA have incentive reinforcement designs, they have caused significant price fluctuations across multiple rounds of interaction, leading to slow system convergence and increased computational load. CAGMM demonstrates a balanced performance in managing quotation fluctuations and enhancing matching stability, showcasing an effective content-driven mechanism advantage. AOMDT's overall performance across the above metrics demonstrates its ability to maintain efficient, stable, and user-friendly market characteristics in a multi-round game environment.

To assess the adaptability and incentive balance of algorithms with changing privacy preferences, scenarios with low, medium, and high privacy levels are created to evaluate their performance across dimensions such as platform revenue, buyer utility, seller utility, and incentive imbalance. The results are shown in Fig. 9.

In Fig.9(a), AOMDT and CAGMM achieved buyer utility of 32.26 and 30.99, respectively, and could still provide strong incentives at medium privacy levels. In Fig. 9(b), the trend of seller utility was consistent with that of buyer utility, with AOMDT and CAGMM utilities of 33.38 and 31.51, respectively, verifying their ability to control overall match fairness. In Fig. 9(c), under different privacy preferences, the average platform revenue of AOMDT at high privacy levels was 25.27, higher than SADAM's 23.58 and HIMA's 21.93. In Fig. 9(d), the incentive imbalance index (IBI) showed an increasing trend with the increase of privacy level. In high privacy scenarios, the IBI of AOMDT was 0.021, indicating that AOMDT had better compatibility and game stability when facing participant heterogeneity preferences. Meanwhile, a typical privacy-efficiency trade-off can be observed: stronger privacy preferences usually lead participants to adopt more conservative bidding strategies, thereby reducing immediate social welfare and platform revenue. However, AOMDT, through its privacy discount factor and stability screening mechanism, maintains a high level of utility and revenue even in high-privacy scenarios, demonstrating its ability to maintain high market efficiency while protecting user privacy.

Table. 2. Comparison of stability performance after convergence of multiple rounds of games

Model	Social Welfare (SW)	Match Rate (MR)	Average Bid Change (ABR)	Average Calculation Time (s)
AOMDT	105.3	0.85	0.037	1.43
FLAM	98.7	0.80	0.058	2.35
BDA	96.2	0.82	0.051	2.17
PMAA	97.8	0.83	0.043	1.72
SADAM	101.4	0.84	0.039	1.89
HIMA	100.2	0.83	0.045	2.10
CAGMM	102.6	0.84	0.041	1.76

To evaluate the pricing fairness and responsiveness of various models to high-privacy users under different transaction structures, three types of bid asymmetrical scenarios are set up. A1 is an equilibrium market where the bids of both buyers and sellers are basically symmetrical, A2 represents a mildly imbalanced market where the bids have moderate deviations, and A3 simulates a highly asymmetric market where the bids deviate significantly. The test results are shown in Fig. 10.

In Fig. 10(a), the price deviation indices of AOMDT, SADAM, HIMA, and CAGMM in highly asymmetric scenarios were 0.060, 0.072, 0.086, and 0.067, respectively. AOMDT's price regulation mechanism can effectively suppress transaction deviation when the bidding structure is imbalanced. In Fig. 10(b), the engagement rates of high-privacy users in the A3 scenario were 0.870, 0.800, 0.760, and 0.824, respectively. In contrast, HIMA lacks targeted regulation, resulting in a more severe imbalance of user incentives under extreme conditions. Although CAGMM can match content, there is still incentive attenuation in the context of asymmetric bidding. From a user's perspective, the price deviation index represents the degree of deviation between the transaction price and the participant's true valuation. The lower the value, the fairer the transaction. Meanwhile, a high privacy-focused user participation rate reflects the algorithm's incentive compatibility in protecting vulnerable groups or privacy-sensitive users. AOMDT's robust performance on both metrics demonstrates its ability to balance fairness, participation, and adaptability to extreme market structures.

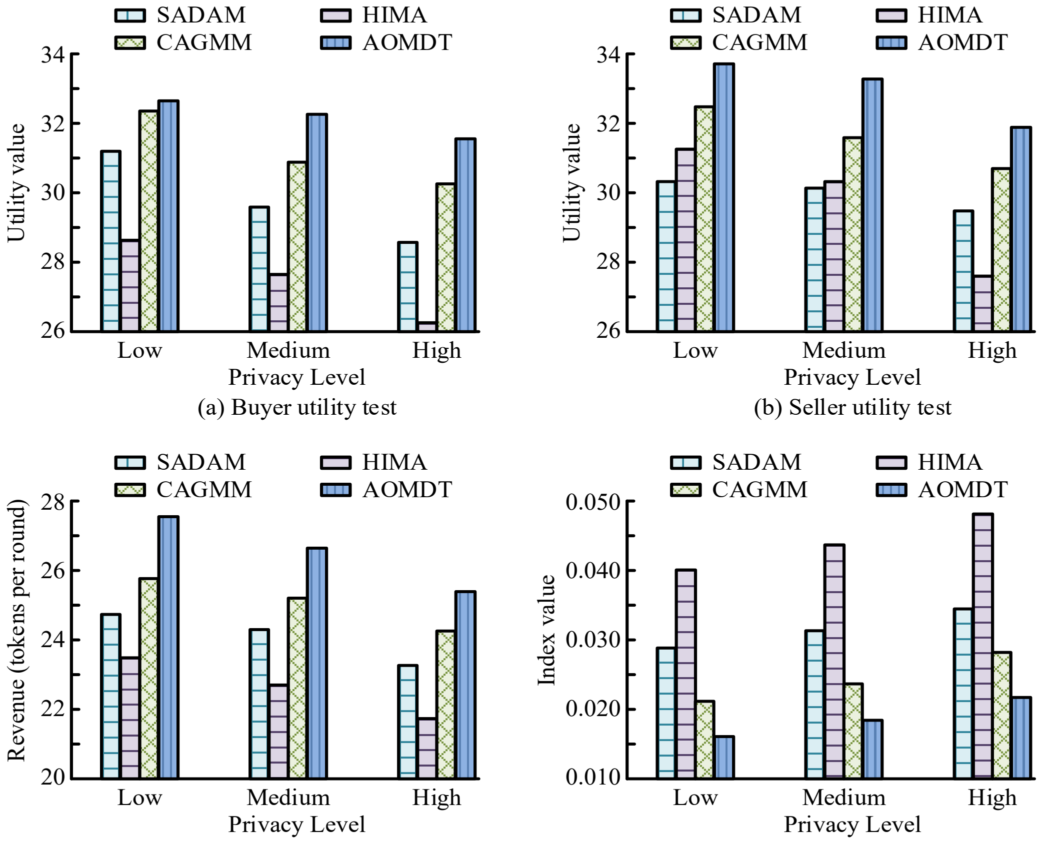


Fig. 9. Platform revenue and incentive balance test

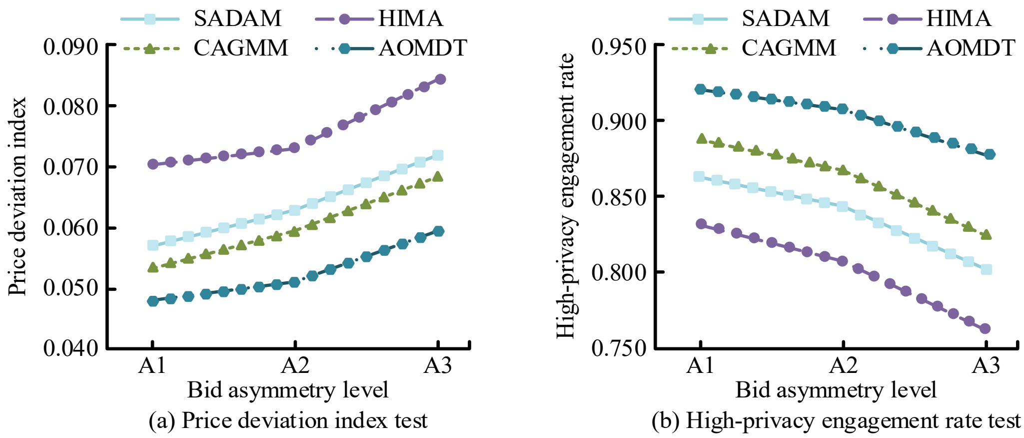


Fig. 10. Test results under different bidding asymmetry scenarios

4. Conclusion

Addressing issues of low matching efficiency, unstable incentive mechanisms under privacy constraints, and opaque transaction pricing strategies in many-to-many data transactions, an auction-driven data transaction optimization algorithm called AOMDT was developed. In the parameter sensitivity test, the combination with a privacy regulation mechanism of 0.5 and a threshold of 0.06 performed the best. The ablation experiment confirmed the effectiveness of each module of the AOMDT algorithm. When the market size reached S5, the average response times of AOMDT, FLAM, BDA, and PMAA were 12.4, 14.2, 13.8, and 13.0 seconds, respectively, with pairing stability rates of 0.85, 0.80, 0.82, and 0.83, respectively. In application testing, AOMDT achieved a social welfare of 105.3, a match rate of 0.85, an average bid change of 0.037, and an average calculation time of 1.43 seconds. Under low, medium, and high privacy levels, the buyer utilities of AOMDT were 32.72, 32.26, and 31.47, respectively.

To strengthen its practical relevance, this work further discusses how the proposed mechanism can be integrated into real digital trading environments. The incentive-compatible pricing strategy and stability-aware matching process make AOMDT suitable for adoption in Internet of Things (IoT) data markets, digital advertising exchanges, and smart city data-sharing platforms, where heterogeneous participants frequently interact. In Web 3.0 or decentralized data-exchange settings, AOMDT can operate as a governance layer or matching engine to support fair, privacy-aware, and automated data transactions among distributed stakeholders. These application scenarios illustrate the potential usability of the algorithm for businesses, data brokers, and online platforms seeking to improve fairness, transparency, and market efficiency.

Although the AOMDT algorithm demonstrates good stability and incentive compatibility in many-to-many data transactions, some limitations remain. First, parameter settings depend on offline tuning and are difficult to adapt to policy changes in dynamic environments. Second, the model has not yet incorporated more complex heterogeneous behaviors and real game preferences, which may impact its applicability and generalizability. Additionally, the current implementation has not been optimized for high-concurrency environments, leaving room for improvement in computational efficiency. Future work could introduce adaptive learning mechanisms to improve model flexibility, enhance behavior modeling accuracy, and integrate privacy protection technologies to realize a more efficient and secure data transaction framework.

Author Contributions

Haoming Yan contributes to conceptualization, methodology, software, analysis, data collection, draft preparation, and manuscript editing. Yang Liu contributes to analysis, investigation, data collection, and visualization. All authors have read and agreed with the manuscript before its submission and publication.

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