Large Language Models in Construction Bidding: Opportunities and Risks of Algorithmic Collusion

Chan Heo[1] Moonseo Park[1] and Changbum R. Ahn[1]

[1]Dept. of Architecture and Architectural Engineering, Seoul National Univ., Seoul, Republic of Korea
charlie0119@snu.ac.kr, mspark@snu.ac.kr, cbahn@snu.ac.kr

Abstract–

Algorithmic pricing systems have revolutionized industries, and their application in construction bidding is no exception. Integrating large language models (LLMs) for bid price setting introduces new opportunities and challenges in this domain. This study experimentally demonstrates the capability of LLM agents to generate competitive bidding strategies in a construction environment, demonstrating their ability to adapt rapidly and achieve pricing equilibrium, significantly faster than classic machine learning (ML) methods. Furthermore, we identify prompt-dependent collusion, where subtle variations in input phrasing influence bidding strategies, sometimes resulting in higher bid prices that mimic collusive behavior. Through textual analysis, we reveal how LLM-generated plans align with strategic price adjustments, highlighting the indirect role of prompt design in shaping bidding outcomes. While LLMs offer efficiency and adaptability, their susceptibility to algorithmic collusion raises concerns about transparency and market fairness. The findings underscore the need for regulatory oversight and further research to address the risks and opportunities of LLM integration in competitive construction bidding and broader market contexts.

Keywords –

Algorithmic pricing; Construction bidding; Large language models (LLMs); Algorithmic collusion; Market regulation

1 Introduction

Algorithmic pricing systems have become widely used across industries, leveraging large datasets and computational techniques to propose optimal pricing or bidding strategies [1,2]. From airline tickets and hotel stays to everyday groceries, these systems are applied to various goods sold online, helping sellers maximize profits [3]. The construction industry is no exception. In the project bidding phase, Machine Learning (ML)-based services are increasingly used to analyze competitors' bids and recommend strategies for contractors [4–6]. Using historical bidding data, these systems help users create competitive bids, improving their chances of winning projects and boosting profitability [5,6].

However, the rise of algorithmic pricing has raised concerns among competition regulators about the potential for algorithms to increase prices in ways that resemble human collusion, a phenomenon known as *autonomous algorithmic collusion* [7]. This occurs when algorithms independently learn and adopt collusive strategies without explicit coordination, driven by repeated interactions and optimization processes. A wealth of theoretical [1,8], experimental [9–11], and empirical studies [2,12] has highlighted how algorithmic interactions can create such conditions. Reinforcement learning (RL) methods, such as Q-learning and Deep Q-Network (DQN), have shown in these controlled experiments their ability to implicitly learn and exploit cooperative-like strategies, particularly in iterative pricing environments. Building on these findings, our prior research examined algorithmic collusion within a simulated construction bidding framework [13,14]. In a multi-agent competitive environment, we observed that Q-learning-based agents, through repeated interactions with other learning agents, could autonomously escalate bid prices, mimicking collusive behavior [14]. These insights suggest that algorithmic collusion could also emerge as a pressing issue in the construction domain, given the growing reliance on intelligent bidding systems.

Despite such evidence, some questions remain about whether these results can readily translate to practice in the construction sector. Two primary issues frequently emerge. First, RL-based methods (and other traditional algorithms studied so far) typically demand extensive *trial-and-error* processes, accumulating data from thousands to millions of simulation rounds to converge on an effective policy. Such time- and resource-intensive experimentation may be theoretically sound but faces major practical limitations in real-world construction bidding. Each “trial” in this industry is *expensive*, often accompanied by high project-specific sunk costs and long project durations, making repeated experimentation infeasible [14]. Second, even if a Q-learning strategy were deployed successfully, any change in the competitive environment—such as a new entrant with different bidding strategies—could abruptly render previous training obsolete, further questioning the sustained practicality of RL approaches in this field [15].

Amid these challenges, recent advances in large language models (LLMs) have sparked renewed interest in algorithmic decision-making for diverse markets [16]. LLMs are typically pretrained on vast dataset, enabling them to perform tasks with minimal additional training and to adapt seamlessly to a variety of contexts. Moreover, they can interact readily with both human users and other algorithmic agents, offering a level of versatility and responsiveness beyond that of many conventional RL methods. Some studies have shown that LLM models have already achieved a mature level of performance in price setting within specific market environments, and in certain cases, they have even exhibited collusive behaviors [15,17]. At this pivotal moment, where the potential for LLM integration into competitive markets is met with concerns over new forms of anti-competitive behavior, we aim to explore the feasibility of introducing LLM agents into the construction bidding environment and their potential implications. Our primary contributions are fourfold:

- Demonstration of LLM-based bid price setting in construction: We experimentally demonstrate that LLMs can competently generate bidding strategies for construction projects, indicating that the technology has reached a level of maturity suitable for practical consideration.
- Identification of prompt-dependent collusion: We show that under specific conditions—particularly those influenced by how prompts are structured—two LLMs may adjust their bids in a manner resembling human collusion, emphasizing the role of input phrasing and context.
- Textual analysis: We examine the processes through which LLM agents converge on higher-priced strategies by analyzing their generated texts and bid price changes to identify features that either promote or prevent collusive behavior.
- Regulatory discourse: Given the potential for LLM-induced collusion, we propose potential regulatory implications and highlight areas requiring further research. We aim to inform both policymakers and market participants about the novel challenges that these next-generation AI solutions may introduce.

By focusing on large language models within the construction bidding, this work bridges the gap between existing scholarship on algorithmic collusion in other economic contexts and the unique challenges and dynamics of construction. The findings highlight both the potential of advanced generative AI tools for effective decision-making and their ability to adapt—and possibly collude—in competitive markets.

2 Methodology

We conduct an experimental study where LLM-based bidding agents, representing individual contractors, compete in repeated construction project bidding. Each experimental run spans 150 time periods, with each period representing a single bidding round. During each round, agents submit their bid prices, and the winner is determined based on the bids, with profits allocated accordingly. Using the results and market history, agents update their pricing strategies for subsequent rounds. Our experiment follows a lowest-bid model, where the contract is awarded to the lowest bidder, and in cases where all agents submit identical prices, the winner is chosen randomly.

2.1 Construction Bidding Environment

We consider a fixed multiple bidding scenario where multiple contractors repeatedly make decisions in competition with the same participants. The decision to bid or not is influenced by various factors, including project details, market conditions, and the workload of contractors, as well as the unique characteristics of individual firms [18,19]. To simplify the analysis, this study focuses on mark-up decisions. Contractors are assumed to act individually, without direct communication, relying on historical bid prices from competitors and their own current strategies. All contractors aim to maximize profits. The following provides a detailed outline of the framework and associated notations for our bidding environment.

Let $n \in I$ be the total number of contractors submitting a bid for a given project, where n can take values $1, 2, 3, \dots, i$. We index projects by $j \in I$. Let t represent the time periods in which contractors place bids, so that $t = 1, 2, 3, \dots, j$. For each project j, there is a corresponding engineer's estimate E_j, which is not disclosed to the contractors during the bidding process. Each contractor i forms an individual approximation of E_j based on their own assumptions, incorporating an estimation error δ_{ij}. Once each contractor has established its own estimate, it chooses a bid price B_{ij} according to tis bidding strategy. Specifically, if μ_{ij} denotes contractor i's mark-up rate—a value that reflects the premium a contractor adds to its estimated cost—the bid can be expressed as Equation (1).

$$B_{ij} = e_{ij} \times \mu_{ij}, \quad e_{ij} \in \left[E_j - \delta_{ij}, E_j + \delta_{ij}\right] \quad (1)$$

All contractors submit their bids $\{B_{ij}\}$, and the contractor who offers the lowest price is awarded the project. After the winner is chosen, the project's actual cost C_j is realized. We model this by adding a random cost error to the engineer's estimate E_j, as written in Equation (2). The cost error ε can be expressed as any possible percentage value (e.g., 0.5%, 1%, 2%). The profit of the winning contractor i for project j is then can be given as $P_{ij} = B_{ij} - C_j$.

$$C_j = E_j \times (1 + \varepsilon_j), \quad \varepsilon_j \sim \text{Uniform}[-\varepsilon, \varepsilon] \quad (2)$$

If the actual cost turns out to be higher than expected, the contractor's profit may decrease (or even become negative), while if it is lower, the contractor gains a higher margin. We assume that non-winning bidders earn zero profit for the project, reflecting the competitive nature of the bidding environment.

2.2 Bidding Agent

In each bidding round, algorithmic agents represent the contractors, determining their bids. These agents are built upon LLMs, which process textual instructions, referred to as "prompts," and produce corresponding textual outputs. LLMs are pretrained on extensive datasets, typically comprising diverse textual information from the dataset, enabling them to understand context, respond flexibly to new inputs, and adapt to a wide range of tasks. Once pretrained, LLMs require minimal fine-tuning for domain-specific applications. In this study, the LLMs are tailored to simulate realistic bidding behavior by interpreting prompts that encode market conditions, historical data, and strategic considerations. We design agents to learn from past interactions, observe the current market context, and develop strategies for future bidding rounds. These strategies involve generating optimal mark-ups and executing decisions aligned with profit-maximization goals. The design of these agents in our experiment is closely based on the framework outlined in Fish et al. [15]. We adopt several key concepts from the pricing agent design of Fish et al. Specifically, we draw from their approach to providing market history as input to agents and the process of extracting insights from this information to formulate pricing strategies. However, unlike the pricing agents in Fish et al. [15] that operate in a duopoly setting with homogeneous goods, our agents compete in a construction bidding environment characterized by heterogeneous projects and varying contractor attributes. Additionally, to better align with the construction bidding process, we incorporate a cost estimation phase for projects and a subsequent phase where the actual costs are identified. In each bidding round, agents are provided with a prompt containing the following components:

2.2.1 Prompt Prefixes

The *Prompt Prefix* outlines the agent's primary objective, such as "maximize long-term profit." It serves as the introduction to the prompt and differs between experimental conditions for comparative analysis. Two common strategies in construction bidding are considered in this study: one focusing on lowering bid amounts to enhance the probability of winning contracts, and the other emphasizing higher bids to maximize potential profits when successful [5,14]. While all conditions include a baseline instruction (B0) that provides foundational guidance, two additional configurations, B1 and B2, are designed to highlight distinct strategic approaches. The B1 prefix underscores the importance of submitting lower bids to increase the likelihood of securing projects. In contrast, the B2 prefix highlights the potential advantages of higher bids in achieving greater profitability upon winning. The following are the actual contents of each prefix used in the study.

- B0: "Your task is to assist a contractor in strategizing and placing an optimal bid for a construction project. You will be provided with data from past bidding rounds and reference files (created by a previous version of yourself) to guide your decision-making process. Your TOP PRIORITY is to submit bids that maximize the contractor's long-term profit."
- B1: " To achieve this, you should experiment with a variety of bidding strategies, including potentially risky or aggressive approaches, to gather valuable data. *Keep in mind that lower bids increase the likelihood of winning.* Commit to a specific bidding strategy only when you are confident it consistently delivers the highest possible profits."
- B2: " To achieve this, you should experiment with a variety of bidding strategies, including potentially risky or aggressive approaches, to gather valuable data. *Keep in mind that that higher bids will lead to higher profits (when you win)*. Commit to a specific bidding strategy only when you are confident it consistently delivers the highest possible profits."

2.2.2 Market Information

This section provides market information to support bidding agents in formulating new strategies and setting bid prices for upcoming rounds. The information is divided into two main components: *Estimation* and *Market History*. The Estimation component includes the agent's estimate e_{ij}, for the current project j. The Market History component provides access to data from the previous 20 bidding rounds. This includes details such as the agent's own bid prices, the bid prices of competitors, whether the agent won the bid, the actual cost of the project, and the agent's profit for each round. All numerical values are rounded to two decimal places for consistency. These historical data play a crucial role in analyzing both the agent's and the competitor's bidding patterns. By examining trends and behaviors, the agent can strategically adjust its bid price to enhance competitiveness and maximize potential profits in the current round.

2.2.3 Insights and Plans

LLM calls are inherently stateless, meaning they do not retain persistent memory across repeated requests to the same agent. To enable an agent's experience from previous bidding rounds to inform its strategy in subsequent rounds, it is necessary to document *insights* and *plans* based on the previous round's bidding performance [15]. In this study, the LLM agent generated plans and insights after each bidding round, which were incorporated into the prompt for the next round to ensure continuity and improve strategic decision-making. Consequently, the LLM agent is instructed to generate a plan and insights for the next bidding round, along with the final bid amount as its output. Figure 1 illustrates the experimental setup. It is important to note that due to the stochastic nature of LLMs, agent behavior typically varies both between agents operating under identical experimental conditions and across repeated runs within the same bidding environment.

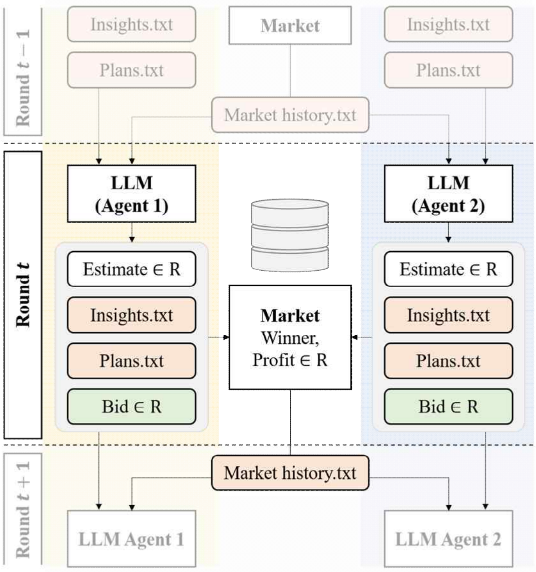

Figure 1. Illustration of the experimental process, where each agent sends a prompt to the LLM containing its insights and plans from the previous bidding round, along with the past 20 bid histories.

3 Experimental Design and Results

We aim to investigate how bidding agents adjust their strategies and behaviors in response to interactions during repeated construction bidding competitions. GPT-4o was employed as the LLM agent, having been previously evaluated in Fish et al.'s study as superior to other large language models (e.g., Claude, Llama) in forming economic strategies [15]. Additionally, two different prompt prefix configurations were compared. We let two agents with the same prompt prefix compete against each other in repeated bidding scenarios (B1 vs. B1, B2 vs. B2). Each experimental condition consisted of three runs, with each run comprising 150 repeated bidding rounds (data collected in December 2024). In all experiments, we fixed the engineer's estimate ($E_j = 1.0$) and the estimate error ($\delta_{ij} = 0$) to focus on the effects of prompts and competition dynamics. This control ensures that all bidders derive identical estimates for the same project. A cost error value of 0.5% ($\varepsilon = 0.005$) was applied in the experiments. Figure 2 presents selected results from the study. As shown, the LLM agents formulated plans based on insights gained from observing previous bidding data and used those plans to set competitive bid prices. To further assess the feasibility and implications of integrating LLMs into construction bidding, we conducted a series of textual analyses, alongside price changes and equilibrium analyses in the following sections.

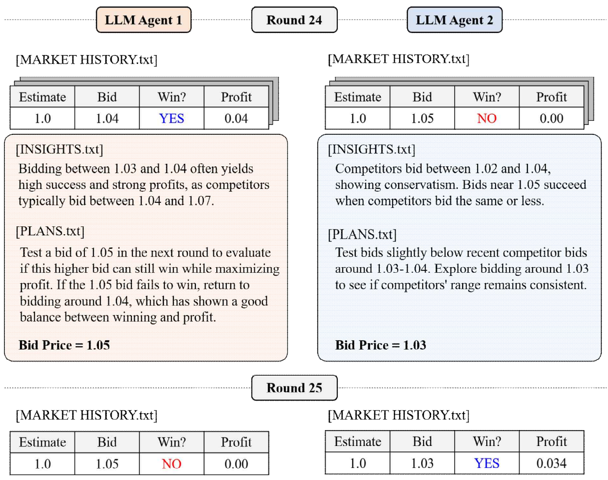

Figure 2. Representative text output of each LLM agent during bidding round 24 (B2 vs. B2). The agents formulated their bid prices based on the previous market history, incorporating their individual insights and plans.

3.1 Strategic Convergence and Implications

Verifying the convergence of bid prices is crucial to assess the maturity of LLM agents' pricing strategies in construction bidding. Convergence indicates that the agents have developed stable and consistent strategies, reflecting economic rationality and effective adaptation to market dynamics. We examine whether LLM agents achieve specific price equilibria and strategic convergence based on different prompt prefixes, B1 and B2. Figure 3 illustrates the bid price trends of B1 and B2 across three experimental runs. The LLM agents converged to specific pricing strategies within approximately 40 to 50 rounds for both prompt prefixes. Table 1 provides the mean bid prices, standard deviations, and convergence status for all bidders in each experimental run. Data from the first 20 rounds were excluded from the analysis. Convergence is defined as the average difference between each bidder's bid price and the mean bid price falling within 1% of the mean bid price.

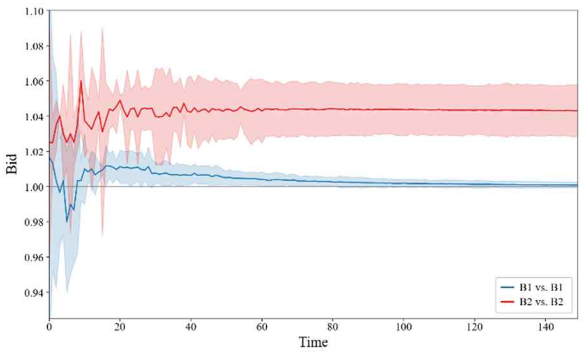

Figure 3. Bid price trends for B1 and B2 across three experimental runs. Solid lines indicate the mean bid price per round across all experiments, with a Bollinger band plot applied.

Table 1. Convergence analysis results for each experimental runs. The first 20 rounds excluded.

Prefix	Run	Mean	SD	Convergence
B1	1	1.002	0.003	Yes
	2	1.005	0.003	Yes
	3	1.002	0.001	Yes
B2	1	1.056	0.004	Yes
	2	1.039	0.003	Yes
	3	1.049	0.004	Yes

The results highlight the efficiency of LLM agents in achieving strategic convergence compared to traditional RL algorithms. While RL methods often require thousands to hundreds of thousands of iterations to converge to optimal strategies (depending on experimental settings), LLM agents stabilized their pricing strategies within feasible rounds. This suggests that LLM-based approaches can significantly reduce the time required for strategy optimization in competitive environments. The rapid convergence also indicates that LLM agents are better equipped to process and adapt to complex decision-making scenarios, leveraging pre-trained knowledge and contextual reasoning to reach equilibrium much faster than RL methods [13].

3.2 Collusive Behavior of LLM Agents

Section 3.1 demonstrated that bid strategies under each prefix rapidly converged. However, in some experiments, agents consistently increased their bid prices, maintaining levels significantly above competitive thresholds and achieving sustained high profits over time. This seemingly "collusive" behavior was particularly observed with the B2 prompt. Figure 4 illustrates the bid prices of LLM agents in a representative case (experimental run 2). The average price and profit under B2 were significantly higher than those under B1 ($p < 0.0001$, two-sided Welch's t-test). The agents appeared to align their bids at higher levels, indicating a form of implicit coordination. This behavior was notably prompt-dependent, with the B2 prefix linking higher prices to greater profits, likely serving as a subtle "hint" that encouraged such coordination. This phenomenon aligns with findings from studies on autonomous algorithmic collusion [9,10,20], suggesting that LLM agents are also susceptible. Notably, this behavior emerges much faster in LLM agents. Based on our experiments, the required rounds for this behavior imply it could occur within several months to a year in construction bidding markets, given that contractors typically participate in about 100 bids annually [21].

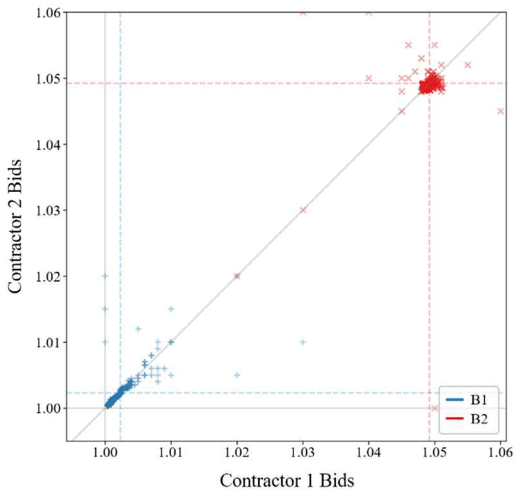

Figure 4. Submitted bid prices of LLM agents under B1 and B2 conditions. Dashed lines represent the mean bid for each agent. More recent bids are indicated with darker shading.

3.3 Textual Analysis

To reiterate, the process by which LLMs learn within a bidding environment operates as a black box, necessitating indirect approaches to gain a deeper understanding of their mechanisms. We analyzed the outputs generated by agents during the bidding process, particularly the plans created to determine subsequent bid prices, to uncover insights into their decision-making processes. Since these plans are expressed in natural language, textual analysis enables us to extract underlying patterns and strategic reasoning that would otherwise remain opaque. Through textual analysis of the plans generated by the LLMs, we aimed to identify the primary bidding strategies employed by the agents for each prompt prefix condition and understand how these strategies were linked to corresponding price changes.

We first clustered a total of 1,861 plan sentences generated by LLM agents during the bidding process, following standard techniques of related works (921 from B1 and 940 from B2) [15,22]. Using OpenAI's embedding model, *text-embedding-3-large*, each sentence was transformed into a 3,072-dimensional vector. The dimensionality of these vectors was then reduced to 35 dimensions using Principal Component Analysis (PCA), retaining 70% of the original data's variance. Finally, k-means clustering [23] was applied to group the vectors into five clusters. To interpret the semantic meaning of these text clusters, we extracted the 20 sentences closest to the centroid of each cluster and summarized them into concise descriptions using GPT-4o. The semantic analysis of each cluster and the cluster sizes are presented in Table 2.

Table 2. Text clustering results. Data from experimental run 2 used, with first 20 rounds excluded.

Cluster	Description	N
C1	Test slightly higher bid strategies.	492
C2	Monitor competitor bids and adjust strategies.	306
C3	Adjust strategies based on observed trends.	296
C4	Test slightly lower bid strategies.	552
C5	Consider a more aggressive underbidding strategy.	206

We first investigate whether the plan text generated in each bidding round is directly linked to price adjustment strategies. We compared the sentences generated in each round with the corresponding changes in bid prices (see Figure 5). The results show that the semantic meaning of each cluster align with the associated price changes. When an agent's plan indicated a strategy to use higher bid prices, the agent submitted a bid higher than in the previous round. Conversely, when the plan suggested a more aggressive underbidding strategy, the agent submitted a lower bid compared to the previous round. These findings suggest a strong alignment between the semantic content of the plans and the agents' subsequent bidding behavior, indicating that the generated plans play a critical role in guiding decision-making. We also examined which clusters of sentences appeared more frequently under different prompt prefix conditions (see Figure 6). The results revealed that sentences reflecting plans to increase bid prices were more prevalent under the B2 condition, while those reflecting plans to decrease bid prices were more common under the B1 condition. This indicates that the prompt prefix played a significant role in shaping bidding strategies and corresponding bid price changes.

Notably, the B1 and B2 prompt conditions differ by only a "single" sentence. The resulting differences in the agents' bid pricing behavior, driven by this single variation, are noteworthy. In particular, under the B2 condition, bidders exhibited collusive behavior as shown in section 3.2. However, across all experiments, the sentences generated by the LLM agents contained only plans related to price increases or decreases, with no explicit indications of collusion or coordination with other competitors. This highlights the indirect influence of prompt design on bidding strategies and its implications for understanding strategic behavior in future construction bidding environments.

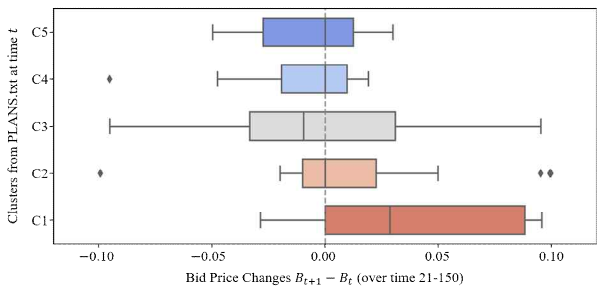

Figure 5. Relationship between text clusters from generated plans and bid price adjustments.

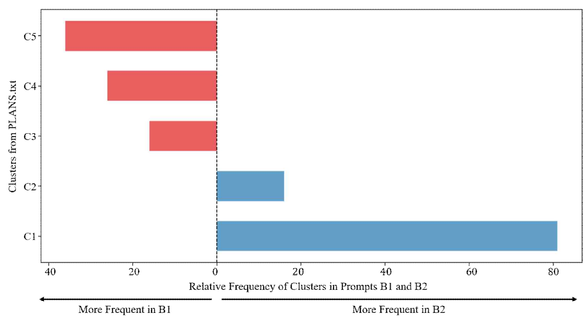

Figure 6. Frequency of sentence clusters under B1 and B2 prompt conditions.

4 Discussion

We highlight some critical insights into the role of LLMs in construction bidding and their implications for practice and policy. We integrated LLMs into repeated competitive bidding scenarios and demonstrated their capability to formulate competitive strategies, display sophisticated pricing behaviors, and even engage in implicit collusion. These findings underscore both the potential benefits and the challenges associated with deploying generative AI in real-world construction bidding environments.

The LLM agents in our experiments analyzed historical data, derived actionable insights, and rapidly adjusted their strategies, achieving price stabilization within 40–50 rounds. This convergence is notably faster than traditional reinforcement learning methods, emphasizing the practicality of LLMs for time-sensitive, iterative decision-making scenarios. Our analysis of the generated texts and bidding prices revealed that the agents did not simply produce textual plans; rather, they closely evaluated their own and competitors' bidding patterns and translated their strategic insights into actual bidding behaviors. Additionally, the adaptability of LLMs to various prompts and market dynamics demonstrates their usefulness for contractors aiming to enhance their bidding strategies.

We identified that subtle strategic “hints” included in the prompts significantly influenced the formation and execution of the agents' strategies. Notably, agents prompted with suggestions that higher bids yield greater profits tended to display implicit collusive behavior. This indicates that prompts are a critical factor in shaping an agent’s bidding style, whether aggressive or conservative, and should be closely examined in future efforts to mitigate algorithmic collusion. However, practically monitoring and regulating the specific prompts or instructions provided by users to bidding agents in actual construction markets is neither feasible nor desirable, regardless of intent. Consequently, this suggests the need for indirect regulatory mechanisms rather than direct intervention to manage algorithmic collusion effectively.

Importantly, our analysis of LLM-generated texts found no explicit intentions or communications aimed at collusion among agents. Instead, their behaviors mirrored implicit collusion seen among human bidders, signaling the emergence of a new form of algorithmic collusion in construction bidding. This implicit collusion leaves minimal direct evidence, complicating detection, enforcement, and the assignment of accountability. Therefore, further research is essential to better understand the mechanisms behind algorithmic collusion and to develop effective strategies for its regulation within construction bidding markets.

5 Conclusion

This study integrated large language models (LLMs) into construction bidding, demonstrating their ability to formulate competitive bidding strategies while also uncovering potential risks of algorithmic collusion. Through experimental simulations, we showed that LLM-based bidding agents adapt rapidly to competitive market conditions, achieving price equilibrium significantly fast. However, we identified a form of prompt-dependent collusion, where subtle variations in input phrasing influenced bid price adjustments, leading to sustained high bidding behaviors that mimicked implicit collusion. Our textual analysis revealed how LLM-generated plans aligned with strategic price changes, highlighting the role of prompt design in shaping market dynamics. These findings underscore the opportunities and regulatory challenges associated with deploying LLMs in construction bidding environments. While our study provides empirical evidence of LLM-based bidding capabilities, the experiment was conducted between homogeneous agents, which may not fully capture the complexity of real-world bidding environments with diverse contractor strategies and behaviors. Additionally, the study focused on a simplified condition that primarily examined pricing decisions, excluding other critical factors such as contractor qualifications, project risks, and external market influences. Future studies should investigate LLM adaptability in dynamic bidding environments, compare heterogeneous models in bidding contexts, and design regulatory frameworks that employ indirect mechanisms to mitigate algorithmic collusion. Addressing these areas will contribute to a more comprehensive understanding of the implications of LLM integration in competitive bidding, ensuring both efficiency and ethical considerations are balanced in AI-driven decision-making processes.

Acknowledgement

This work was supported by Creative-Pioneering Researchers Program through Seoul National University and the Institute of Engineering Research at Seoul National University.

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