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The Strategic Value of AI Capability in Public Procurement Markets: Institutional Alignment and Bid Performance

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[Abstract]

This study examines how AI capability creates strategic value in public procurement markets by integrating the institution-based view with dynamic capabilities theory. Using PLS-SEM with 228 managers from public-procurement-related industries and 5,000 bootstrap resamples, we find that AI capability significantly strengthens institutional alignment (β = 0.194) and execution speed (β = 0.183), whereas its effect on strategic accuracy is non-significant (β = 0.106). Institutional alignment is the primary predictor of bid success (β = 0.255, $p < .001$), while competitive positioning does not significantly predict it (β = 0.062, p = .337), and the AI capability × institutional alignment interaction is also non-significant (β = 0.090, p = .105). Mediation analysis further shows that AI capability creates value primarily through institutional alignment, with a significant indirect effect on bid success (indirect = 0.050, 95% CI [.012, .103]). These findings suggest that AI capability generates strategic value in regulated markets chiefly by strengthening institutional alignment rather than by improving competitive positioning alone.

▸ **Key words**: AI Capability, Information Processing Capability, Institutional Alignment, Competitive Positioning, Bid Success Rate, Public Procurement, PLS-SEM

[요 약]

본 연구는 AI 역량이 공공조달 시장에서 전략적 가치를 창출하는 메커니즘을 제도기반관점(institution-based view)과 동적역량이론(dynamic capabilities theory)을 통합적으로 적용하여 규명한다. 공공조달 관련 산업에 종사하는 관리자 228명을 대상으로 PLS-SEM 분석(부트스트랩 5,000회 재표본추출)을 실시하였다. 분석 결과, AI 역량은 제도적 정합성에 가장 강한 정(+)의 영향을 미쳤으며(β=.378), 이어 전략적 정확성(β=.274), 실행 속도(β=.221) 순으로 나타났다. 제도적 정합성은 낙찰률을 유의하게 제고한 반면(β=.370, $p<.001$), 경쟁적 포지셔닝은 유의한 영향을 보이지 않았다(β=.078, p=.211). 또한 AI 역량과 제도적 정합성의 상호작용 효과가 유의하게 나타나(β=.143, p=.013) 조절된 매개(moderated mediation) 구조를 지지하였고, 가우시안 코퓰러(Gaussian copula) 및 ULMC 검정을 통해 분석 결과의 강건성을 확인하였다. 이러한 결과는 규제 시장에서 경쟁우위만으로는 제도적 순응 없이 조달 성과를 설명할 수 없으며, 제도적 순응이 AI 역량의 전략적 가치 창출을 매개하는 핵심 기제임을 시사한다.

▸ **주제어**: AI 역량, 정보처리역량, 제도적 정합성, 경쟁적 포지셔닝, 낙찰률, 공공조달, PLS-SEM

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I. Introduction

Public procurement markets have long been recognized in industrial-marketing research as structurally distinct from ordinary competitive markets [1],[2]. In these markets, competitive success depends not only on market capability but also on alignment with government policy, responsiveness to regulatory change, and an accurate reading of public requirements. Although algorithm-based decision making is widely expected to reshape market structures [3],[4], how AI capability shapes competitive outcomes in rule-dense institutional markets remains underexplored.

Most research on AI capability has examined value creation in open markets [5],[6]. From an information-systems perspective, AI capability is conceptualized as an organizational information-processing capability that uses machine learning and natural language processing to analyze policy documents, detect regulatory signals, and extract procurement requirements. Institutional markets (public procurement, regulated industries, and government contracting) activate different competitive mechanisms [1]. Where conformity with institutional requirements is decisive, the path from AI capability to competitive positioning may itself depend on the institutional context.

1. Research Gap and Core Questions

Prior work identifies a general mechanism in which AI capability shapes competitive position through strategy execution [7]. Three gaps remain in institutional settings. First, the integration of AI into procurement is still nascent [8], and the execution paths through which AI's competitive value is realized have not been specified. Second, no study has conceptually separated being judged competitively advantageous from actually winning a bid, or empirically traced the conversion between the two. Third, whether institutional alignment acts as a boundary condition on the effect of AI capability has not been tested.

2. Contributions of the Study

This study offers theoretical, methodological, and practical contributions. Theoretically, it joins the institution-based view [1] with research on AI capability [7] to show that institutional alignment mediates the link from AI capability to competitive positioning and, ultimately, to realized performance. Methodologically, it separates competitive positioning (perceived standing) from the bid success rate (realized outcome) within a single procurement model. Practically, it provides guidance for managers seeking to improve procurement performance through AI investment.

II. Theoretical Background

1. The Institution-Based View and AI Capability

Under the institution-based view [1], a firm's strategic choices are shaped by formal and informal institutions, and the ability to exploit these conditions differentiates performance [2]. Dynamic capabilities theory explains how firms renew their capability portfolios as environments change [9]; Teece [10] specified sensing, seizing, and transforming as its sub-processes. Eisenhardt and Martin [11] argued that dynamic capabilities take different forms with market dynamism, and Pisano [12] advanced a prescriptive account. AI can strengthen institutional strategy by monitoring policy shifts in real time and detecting patterns in regulatory requirements [5],[6]. In procurement, the institution-based view accounts for the external determinants of success while dynamic capabilities theory accounts for internal capability renewal, and AI capability is the information-processing capability that links them. Its sensing function, applied to policy and tender documents, captures regulatory signals as they emerge and thereby strengthens institutional alignment, the mechanism we foreground.

In this study, the instrument captures the general degree of AI integration (Appendix, AIC1–AIC4) rather than institution-specific processing as such. We therefore conceptualize AI capability as a general information-processing capability and examine empirically whether, among the three conversion paths, it translates most strongly into institutional alignment; directly operationalizing an institution-specific AI capability remains a task for future research.

2. Distinguishing Competitive Positioning from Realized Performance

In this study, competitive positioning denotes a firm's relative standing and its likelihood of being preferred by buyers, conceptually distinct from winning a bid, which is the realized outcome. Being rated favorably and being selected are related but not identical [13]. The distinction matters most in institutional markets, where formal criteria and rules govern the final choice [14],[15].

3. Strategy Execution and Institutional Alignment

The speed and accuracy of execution shape how a firm is perceived [16], and AI-based decision support can improve both [17]. Strategic accuracy is the fit between strategy and market or task requirements, whereas institutional alignment is the fit between the organization and government policy, the regulatory system, and public requirements. The two capture different dimensions of capability.

4. The Mediating Role of Institutional Alignment

In our model, institutional alignment mediates the effect of AI capability on competitive positioning (H3 → H6) and, as the most influential antecedent of realized performance, links AI capability to the bid success rate. AI capability raises institutional alignment through policy document analysis and the anticipation of regulatory change, which in turn strengthens competitive positioning. We also tested whether institutional alignment moderates the direct AI-capability → competitive-positioning path (H8), following moderated-path analysis [18]. Because this interaction was non-significant (Section V), we retain institutional alignment as a mediator rather than a moderator.

III. Hypothesis Development

Fig. 1 presents the research model. Execution speed, strategic accuracy, and institutional alignment are each regressed on AI capability and the control variables; competitive positioning is regressed on the three mediators, on AI capability, and on the AI-capability × institutional-alignment interaction; and the bid success rate is regressed on competitive positioning and institutional alignment.

H1: AI capability positively affects execution speed. H2: AI capability positively affects strategic accuracy. H3: AI capability positively affects institutional alignment.

H4: Execution speed positively affects competitive positioning. H5: Strategic accuracy positively affects competitive positioning. H6: Institutional alignment positively affects competitive positioning.

H7a–H7c: Execution speed (H7a), strategic accuracy (H7b), and institutional alignment (H7c) each mediate the relationship between AI capability and competitive positioning.

H8: Higher institutional alignment strengthens the effect of AI capability on competitive positioning. H9a: Competitive positioning positively affects the bid success rate. H9b: Institutional alignment positively affects the bid success rate.

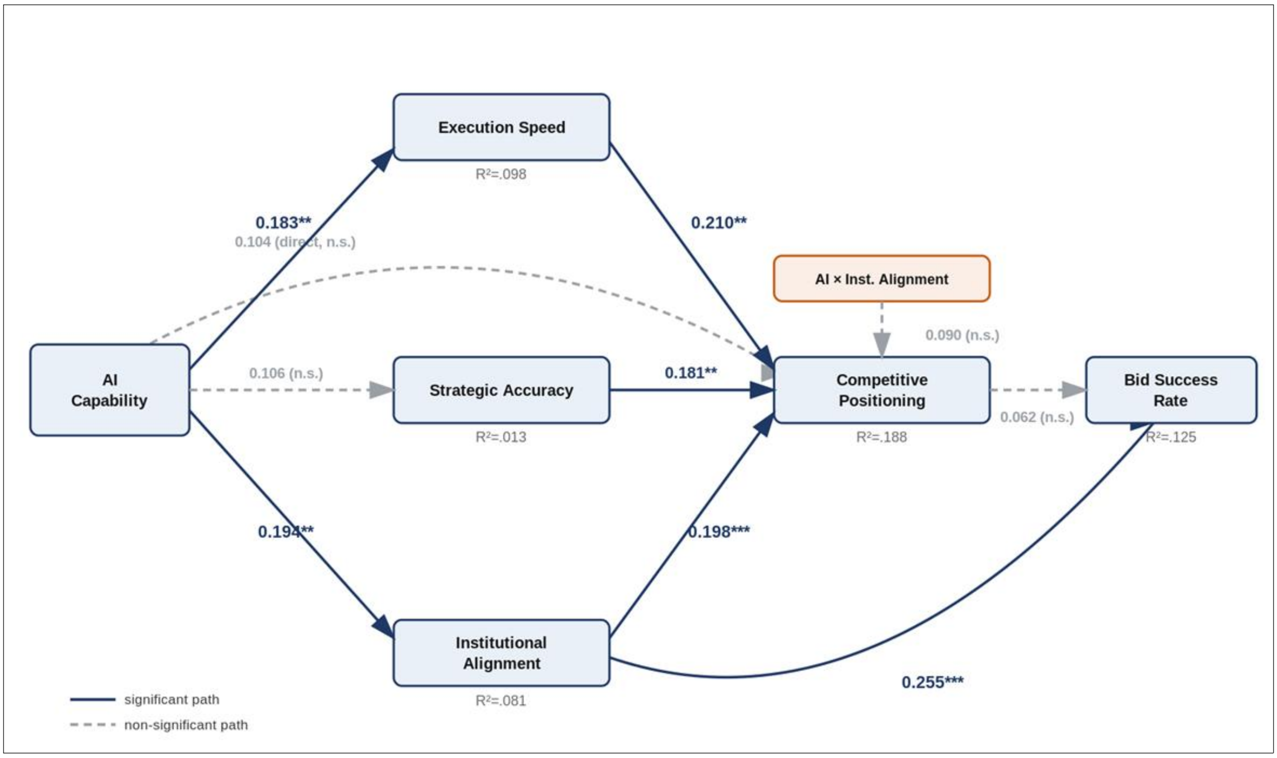

Fig. 1. Conceptual research model and empirical results

IV. Research Method

1. Sample and Data Collection

An online survey ran from March to April 2026 among managers of firms active in institutional markets, using purposive sampling of managerial respondents in public-procurement-related industries. Of 263 returned questionnaires, 35 were discarded according to pre-specified screening criteria (completion time below a minimum threshold, straight-lining across item blocks, or failed attention-check items), leaving 228 valid cases (86.7%). By rank, the sample comprised 55 deputy general managers (24.1%), 51 department or team heads (22.4%), 45 directors or executives (19.7%), 42 assistant managers (18.4%), and 35 managers (15.4%). By size, it included 48 small firms (fewer than 50 employees, 21.1%), 80 lower-mid-sized firms (50–99, 35.1%), 63 mid-sized firms (100–299, 27.6%), and 37 large firms (300 or more, 16.2%). Mean industry experience was 9.6 years (SD = 5.1) and mean AI use was 5.5 times per week (SD = 2.1). Public-market experience was reported by 53.5% of respondents (122); 46.5% (106) had none. Experience was measured at the respondent level (prior personal involvement in public-procurement work); all sampled firms were active in public-procurement-related industries, so items on firm-level constructs such as the bid success rate refer to the firm's track record rather than to the respondent's personal experience. A t-test found no group difference in execution speed, strategic accuracy, or competitive positioning (all $p > .10$), whereas institutional alignment and the bid success rate did differ. To confirm that the inexperienced subgroup did not drive the results, we re-estimated the model on the experienced-only subsample and ran a PLS multi-group analysis (Section V.6).

2. Measurement Instruments

All constructs used 7-point Likert scales. Items were written in Korean and checked for semantic equivalence by back-translation. The three institutional-alignment items were finalized after expert review (I-CVI ≥ 0.80). The four AI-capability items were adapted from Mikalef and Gupta [7] and Mikalef et al. [19]. The three bid-success-rate items were self-reported over the preceding two years. The Appendix lists all items.

3. Analysis Method

We estimated the model with PLS-SEM (SmartPLS 4.0 [20]) for several reasons [21]: the study is prediction-oriented; the model is complex, combining several mediating paths with a latent interaction term and estimated on a moderate sample (n = 228), where PLS-SEM offers stability and power; the data are not multivariate normal; and the study extends an established framework to a new institutional setting. Significance was assessed with 5,000 bootstrap resamples. We evaluated the measurement model with convergent validity (loadings ≥ 0.708, AVE ≥ 0.50, CR ≥ 0.70) and discriminant validity (HTMT < 0.85) [21],[22], and generated the interaction term with the two-stage approach [23]; effect sizes were interpreted with Cohen's f^2 benchmarks [24]. Common method bias was unlikely [25]: Harman's single factor explained 22.7% of the variance, and the maximum full-collinearity VIF was 1.19, well below 3.3 [26].

All constructs were modeled reflectively; construct scores were obtained with Mode A and the path-weighting scheme, with significance from 5,000 bootstrap resamples on the raw data (n = 228).

V. Results

1. Measurement Model

All outer loadings were at least 0.832. Cronbach's α ranged from 0.859 to 0.901, ρ_A from 0.864 to 0.938, composite reliability from 0.912 to 0.932, and AVE from 0.755 to 0.821, each above its threshold. The bid-success-rate construct, in particular, was reliable (α = 0.865, ρ_A = 0.938, CR = 0.916, AVE = 0.784). Discriminant validity held: every HTMT value was below 0.85, the highest being 0.329 (BSR-IA). Although one strategic-accuracy item (ACC1) refers to decision success rates, the ACC-BSR HTMT was among the lowest in the matrix (0.04), indicating no problematic content overlap with the bid-success items. Table 1 reports the measurement model, and Table 2 reports construct descriptive statistics and the full HTMT matrix.

2. Structural Model and Hypothesis Tests

Explained variance was R^2 = 0.098 for execution speed, 0.013 for strategic accuracy, 0.081 for institutional alignment, 0.188 for competitive positioning, and 0.125 for the bid success rate. The model fit the data well (SRMR = 0.046) and showed predictive relevance for every endogenous construct (Q^2 = 0.079 for execution speed, 0.009 for strategic accuracy, 0.059 for institutional alignment, 0.144 for competitive positioning, and 0.079 for the bid success rate). AI capability

Table 1. Measurement Model

Construct	Loadings	Cronbach α	ρ_A	CR	AVE
AIC	0.854-0.888	0.901	0.911	0.930	0.770
SPD	0.896-0.920	0.891	0.894	0.932	0.821
ACC	0.832-0.925	0.859	0.927	0.912	0.776
IA	0.869-0.894	0.861	0.864	0.915	0.783
CP	0.867-0.872	0.893	0.900	0.925	0.755
BSR	0.839-0.927	0.865	0.938	0.916	0.784

Table 2. Descriptive Statistics and Discriminant Validity (HTMT)

Construct	M	SD	1	2	3	4	5
AI capability (AIC)	4.98	0.84	–				
Execution speed (SPD)	4.77	0.93	0.18	–			
Strategic accuracy (ACC)	4.63	0.83	0.11	0.13	–		
Institutional alignment (IA)	4.61	0.82	0.19	0.06	0.04	–	
Competitive positioning (CP)	4.63	0.89	0.21	0.30	0.23	0.24	–
Bid success rate (BSR)	4.60	0.89	0.10	0.04	0.04	0.33	0.12

Table 3. Structural Model and Hypothesis Tests

Hyp.	Path	β	p	f²	95% CI	Result
H1	AIC → SPD	0.183	.002	0.036	[.065, .302]	Supported
H2	AIC → ACC	0.106	.128	0.011	[-.031, .246]	Rejected
H3	AIC → IA	0.194	.005	0.040	[.051, .324]	Supported
H4	SPD → CP	0.210	.002	0.048	[.074, .342]	Supported
H5	ACC → CP	0.181	.001	0.039	[.082, .296]	Supported
H6	IA → CP	0.198	<.001	0.044	[.084, .311]	Supported
H8	AIC×IA → CP	0.090	.105	0.010	[-.020, .194]	Rejected
Direct Effect	AIC → CP (direct)	0.104	.075	0.012	[-.010, .222]	n.s.
H9a	CP → BSR	0.062	.337	0.004	[-.065, .188]	Rejected
H9b	IA → BSR	0.255	<.001	0.068	[.131, .379]	Supported
c1	Ind. experience → SPD	0.246	<.001	-	-	Control
c2	Ind. experience → CP	0.116	.093	-	-	Control
c3	Public-mkt exp. → IA	0.225	<.001	-	-	Control
c4	Public-mkt exp. → BSR	0.130	.040	-	-	Control

significantly raised execution speed ($\beta = 0.183$, $p = .002$; H1) and institutional alignment ($\beta = 0.194$, $p = .005$; H3) but not strategic accuracy ($\beta = 0.106$, $p = .128$; H2 rejected). Execution speed ($\beta = 0.210$, $p = .002$; H4), strategic accuracy ($\beta = 0.181$, $p = .001$; H5), and institutional alignment ($\beta = 0.198$, $p < .001$; H6) each predicted competitive positioning, whereas the direct effect of AI capability on competitive positioning was non-significant ($\beta = 0.104$, $p = .075$). Table 3 reports the structural model.

3. Competitive Positioning and the Bid Success Rate

Competitive positioning did not significantly predict the bid success rate ($\beta = 0.062$, $p = .337$), so H9a is rejected; institutional alignment was the dominant predictor (H9b: $\beta = 0.255$, $p < .001$, $f^2 = 0.068$). In rule-based institutional markets, then, meeting institutional requirements matters more for selection than overall competitive strength. We read this null result not as evidence that competitive positioning is irrelevant, but as a sign that general competitive strength does not convert into won bids unless institutional requirements are met; sample size and the complexity of procurement may further attenuate this path. Because competitive positioning and the bid success rate are empirically distinct (HTMT well below 0.85), this null is unlikely to be a discriminant-validity artifact; given $n = 228$, however, the path is only modestly powered and is best interpreted as a failure to detect rather than a true zero.

4. Moderation Test

The AI-capability × institutional-alignment interaction was non-significant ($\beta = 0.090$, $p = .105$, $f^2 = 0.010$). Simple-slope analysis placed the conditional effect of AI capability on competitive positioning at $\beta = 0.194$ under high institutional alignment (+1 SD) and $\beta = 0.014$ under low alignment (−1 SD), but the two slopes did not differ significantly. H8 is therefore rejected, and we make no moderated-mediation claim; institutional alignment functions as a mediator in the model.

5. Mediation Analysis

With 5,000 bootstrap resamples and bias-corrected 95% confidence intervals, mediation through execution speed (H7a: 0.038, CI [.009, .081]) and through institutional alignment (H7c: 0.038, CI [.007, .084]) was supported, whereas mediation through strategic accuracy was not (H7b: 0.019, CI [-.006, .056]), consistent with the non-significant AI-capability → accuracy path. The total indirect effect was 0.096 (CI [.049, .163]). Beyond mediation on competitive positioning, the two-step path from AI capability to realized performance through institutional alignment was also significant (AI capability → institutional alignment → bid success rate; indirect = 0.050, bias-corrected 95% CI [.012, .103], $p = .035$), which directly substantiates institutional alignment as the conversion channel to won bids. Table 4 reports the details.

Table 4. Mediation Effects

Hyp.	Indirect path	β	95% CI	Result
H7a	AIC → SPD → CP	0.038	[.009, .081]	Supported
H7b	AIC → ACC → CP	0.019	[-.006, .056]	Rejected
H7c	AIC → IA → CP	0.038	[.007, .084]	Supported
-	AIC → IA → BSR (two-step)	0.050	[.012, .103]	Supported
-	Total indirect (on CP)	0.096	[.049, .163]	Supported

6. Control Variables and Robustness

Industry experience significantly predicted execution speed ($\beta = 0.246$, $p < .001$) and, though not significant, competitive positioning ($\beta = 0.116$, $p = .093$). Public-market experience predicted institutional alignment ($\beta = 0.225$, $p < .001$) and the bid success rate ($\beta = 0.130$, $p = .040$). The frequency of AI use predicted none of the endogenous constructs, indicating that the strategic integration of AI, not sheer usage, is what matters. In an experienced-only re-estimation ($n = 122$), institutional alignment remained the key determinant of the bid success rate ($\beta = 0.296$, $p < .001$) and the competitive-positioning-to-bid-success path stayed non-significant ($\beta = 0.070$), preserving the pattern. A PLS multi-group analysis between experienced ($n = 122$) and inexperienced ($n = 106$) respondents revealed no significant difference on any focal path (all $p > .05$), so the findings are not an artifact of inexperienced respondents. A Gaussian-copula test [27] found the copula term for AI capability to be non-significant ($p = .501$), supporting its treatment as exogenous.

VI. Discussion

1. Interpretation of the Findings

Why does institutional alignment, rather than competitive positioning, appear to convert AI capability into realized bid performance? In institutional markets, selection is governed by codified, formal criteria rather than by buyers' discretionary judgments of overall attractiveness. A firm may be rated competitively strong yet still fail to win if it does not conform to tender-specific institutional requirements, hence the near-zero positioning-to-bid path. AI capability helps firms better understand policy requirements and respond more effectively to regulatory changes [5]. This also explains why AI capability did not significantly improve strategic accuracy. This pattern follows from how selection actually works in these markets. Public procurement decisions rely primarily on explicit institutional compliance rather than holistic market-fit judgments. Accordingly, strategic accuracy, which captures market/task fit rather than rule conformity, had little room to mediate AI capability's effect in this rule-governed setting, consistent with its weak explanatory role ($R^2 = 0.013$). In institutional markets, this information-processing capability functions primarily through institutional alignment.

2. Theoretical Contributions

This study distinguishes competitive positioning from realized performance and empirically examines how one relates to the other. This distinction qualifies the conventional logic that links competitive advantage to performance [6],[28]. Unlike previous studies of AI and firm performance, which focused primarily on direct effects, our results show that AI's value emerges mainly through institutional alignment. Execution speed and accuracy both raised competitive positioning, supporting execution theory [16],[29]; however, AI capability did not significantly improve strategic accuracy (H2), so accuracy did not mediate the AI-positioning link (H7b), which bounds the generality of the execution mechanism here.

3. Practical Implications

Overall, these findings suggest that AI creates value not simply by accelerating organizational actions but by enabling firms to interpret and respond to institutional requirements more effectively. These findings carry concrete implications for executives in public procurement: rebalance AI investment to strengthen institutional alignment alongside competitive capability. AI creates value primarily through institutional alignment (NLP-based analysis of policy documents, automated tracking of regulatory change, and extraction of tender requirements [30]) rather than through raw speed. Becoming the firm that best fits the institutional requirements of a specific tender is more effective than simply being a generally strong competitor. Because public-market experience (β = 0.225 for institutional alignment; β = 0.130 for the bid success rate) and AI capability are complementary, developing both together builds durable procurement competitiveness [31].

VII. Limitations and Future Research

This study has several limitations that should be considered when interpreting the findings. First, the cross-sectional design cannot rule out reverse causality; longitudinal, instrumental-variable, or natural-experiment designs would sharpen causal inference. Second, competitive positioning and the bid success rate were self-reported and perceptual; triangulation with archival procurement records would strengthen external validity. Third, AI capability was measured with general-integration items rather than institution-specific AI processing items, which may understate its institutional dimension, so a dedicated scale is a priority. Fourth, because 46.5% of respondents had no procurement experience, replication on an all-experienced sample is warranted, although the multi-group analysis showed no group differences. Fifth, the explained variance and effect sizes are modest (e.g., R^2 = 0.125 for the bid success rate; most f^2 values fall in the small range), so the results are best read as directionally consistent, exploratory evidence rather than as estimates of large effects. Sixth, because all constructs, including the bid success rate, were self-reported by a single respondent per firm in a cross-sectional design, common-method and reverse-causality concerns cannot be fully excluded despite the Harman, full-collinearity, and Gaussian-copula checks; the causal language throughout should accordingly be read as associational. Future work should also validate the institutional-alignment scale through independent EFA/CFA and cross-national comparison. Future research should examine whether institution-specific AI capabilities explain procurement performance better than general AI capability in highly regulated industries such as healthcare, defense, and public infrastructure.

VIII. Conclusion

This study addressed three gaps identified in prior procurement research. First, it specified the execution paths through which AI capability realizes competitive value, showing that AI works through execution speed and, most consistently, institutional alignment. Second, it separated competitive positioning from realized bid performance and traced the conversion between them, showing that competitive positioning alone was not sufficient to significantly predict bid success. Third, it tested institutional alignment as a boundary condition and found no significant moderation, so alignment operates as a mediator rather than a moderator. Across the hypothesis tests, H1, H3, H4, H5, H6, H7a, H7c, and H9b were supported, whereas H2, H7b, H8, and H9a were not. Institutional alignment emerged as the leading predictor of realized bid performance in this model. AI capability appears to operate primarily through institutional alignment (β = 0.194), which is in turn the dominant driver of won bids (β = 0.255). AI capability improves both execution efficiency and institutional alignment, but its contribution to realized procurement performance comes primarily through institutional alignment [5],[6]. Overall, the findings suggest that competitive positioning alone may be insufficient in institutional markets; realized success appears to depend on institutional conformity, so AI strategy should place greater emphasis on alignment with institutional requirements while also supporting execution efficiency.

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APPENDIX. Survey Items

Table A1. Measurement Items

Construct	Item	Measurement item (7-point Likert: 1 = strongly disagree, 7 = strongly agree)
AI Capability (AIC)	AIC1	Our organization integrates AI-based analytics systems into its work processes.
	AIC2	We use AI to forecast market and policy trends.
	AIC3	We use AI to analyze competitive and market information.
	AIC4	AI is integrated into our strategy formulation.
Execution Speed (SPD)	SPD1	We respond more quickly than competitors.
	SPD2	We respond rapidly to market changes.
	SPD3	Our decision-to-execution time is short.
Strategic Accuracy (ACC)	ACC1	Our decisions achieve high success rates.
	ACC2	Our strategies fit market demand.
	ACC3	We rarely need to revise our strategies.
Institutional Alignment (IA)	IA1	We are well aligned with government policy directions.
	IA2	We respond quickly to regulatory change.
	IA3	We understand public procurement requirements well.
Competitive Positioning (CP)	CP1	Our relative position in the market is strong.
	CP2	Buyers are likely to prefer our firm.
	CP3	We are attractive relative to competitors.
	CP4	Our overall market positioning is favorable.
Bid Success Rate (BSR)	BSR1	Our bid win rate is high relative to competitors.
	BSR2	Our public procurement contract award rate is high.
	BSR3	Our track record of public-market awards is strong.