

WHAT DEMAND-MANAGEMENT CONFIGURATIONS IMPROVE PROCUREMENT SATISFACTION IN UNIVERSITIES? A NEURAL-NETWORK-BASED NONLINEAR RECOGNITION AND CSQCA ANALYSIS

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Abstract: After the implementation of procurement demand-management rules, whether university procurement satisfaction improves cannot be explained adequately by any single institutional arrangement or isolated managerial measure. Based on 50 valid questionnaire responses collected in September 2024, this study adopts a sequential mixed analytical design. First, neural-network-based nonlinear recognition is used to assess the independent and joint explanatory capacity of graded review rules, procurement-demand coordination, professional support, financial/audit supervision, flexible review arrangements, and several extended governance-context variables. Second, after the neural-network results show that single-condition and net-effect explanations are insufficient, crisp-set qualitative comparative analysis (csQCA) is used to identify sufficient configurations associated with improved procurement satisfaction. The results show that 82% of the cases report improvement, yet the mean balanced accuracy of single-condition neural-network models is only 0.544, and the balanced accuracy of the five-condition model is 0.470. When whole-process cognition, goal understanding, review-team scale, and other contextual variables are added, the balanced accuracy rises to 0.564 and AUC rises to 0.620, suggesting a limited but meaningful nonlinear configurational space. The csQCA results identify no single necessary condition with adequate discriminating power. Under a frequency threshold of 2, a consistency threshold of 0.85, and conservative minimization without logical remainders, three sufficient paths emerge: professional-flexible compensation, graded coordination-supervision, and professional-led transition. The overall solution consistency is 1.000 and the overall solution coverage is 0.415. The findings suggest that university procurement demand-management reform should move beyond the isolated optimization of rules, experts, or review modes and instead construct matched bundles of classification rules, cross-departmental coordination, expertise, supervision, and procedural adaptation.

Keywords: Universities; Government procurement; Demand management; Procurement satisfaction; Neural-network; CsQCA

1 INTRODUCTION

Government procurement demand management links project objectives, market supply, procurement methods, evaluation criteria, contract clauses, and performance acceptance [1-2]. It is the front-end arena in which the purchaser's responsibility is operationalized [1, 3]. For universities, demand management is not only a compliance gateway but also the mechanism through which technical needs, budgetary constraints, teaching and research objectives, and later use requirements are translated into procurement documents [4].

University procurement is characterized by heterogeneous project types, knowledge-intensive requirements, dispersed demand departments, and strong professional specialization [5]. The same regulatory requirement may therefore generate different implementation structures across universities. Some institutions rely on clear graded review rules to allocate review intensity; others rely on coordination between procurement and demand departments to reduce information loss; some introduce industry experts or third-party organizations to compensate for knowledge gaps; and others embed financial, audit, or oversight actors to strengthen budgetary and accountability constraints [6-7]. At the same time, additional review procedures may also increase coordination time and workload. Satisfaction improvement is therefore not a simple function of stronger control [8-9]. Supplier-facing public procurement research further shows that public agencies must also become attractive and credible customers to strategic suppliers [10]. It depends on whether control benefits, procedural costs, and organizational capacity can be matched.

Existing discussions often approach procurement demand management from the perspectives of legal compliance, purchaser responsibility, or internal control [3, 6]. Empirical accounts commonly present proportions, means, or descriptive comparisons of policy implementation. Such analyses are useful for showing the overall level of perceived improvement, but they are less able to answer two more specific questions. First, can any single condition distinguish whether satisfaction improves? Second, if single-condition explanations are insufficient, what combinations of conditions constitute interpretable implementation paths? This study addresses these questions by asking: which

configurations of university procurement demand-management conditions are associated with improved procurement satisfaction?

The research design follows a logic of nonlinear recognition before configurational explanation [11-12]. Neural-network analysis is first used to examine whether single conditions and candidate condition sets have adequate explanatory capacity. Once the results indicate that standalone explanations are weak and that the outcome has a configurational structure, csQCA is used to identify sufficient paths [13-14]. The purpose is not to replace QCA with a neural network, but to use the neural network to justify the turn from net-effect thinking to configuration-based explanation.

2 CONCEPTUAL DEFINITIONS AND ANALYTICAL FRAMEWORK

2.1 Procurement Satisfaction Improvement as Proximal Role-Based Feedback

Procurement satisfaction improvement is measured by the questionnaire item asking how respondents perceive procurement satisfaction in their own work roles after the implementation of demand-management rules. The item captures a comparative evaluation of the work state before and after implementation. It may reflect perceived legality, demand quality, communication efficiency, review burden, and expected performance outcomes. It is not equivalent to objective procurement performance at the university level and cannot replace indicators such as procurement cycle time, cost savings, supplier competition, contract variation, or acceptance quality. Its analytical value lies in capturing whether demand-management arrangements generate positive feedback among those who execute or participate in procurement work.

2.2 Condition Selection and Mechanisms

Five core conditions are used in the main csQCA model. Graded review rules (GRADE) capture rule precision, that is, whether a university differentiates ordinary review from key review according to project amount, complexity, or project attributes [4]. Procurement-demand coordination (COORD) captures information integration between procurement and user departments. Professional support (PROF) captures the knowledge supplementation provided by industry experts, third-party organizations, or internal professional committees. Financial/audit supervision (SUP) captures the embedding of budget, asset, compliance, and accountability constraints [6, 15]. Flexible review arrangements (FLEX) capture procedural adaptation, including countersignature, online review, correspondence review, third-party review, or hybrid review modes [16-17].

In addition to the five core conditions, the neural-network stage includes extended variables: whether dedicated rules are formulated, whether there is an institutional or procedural response, review-team scale, complete understanding of policy goals, meeting-based review, and whole-process cognition. These variables are not all included in the main QCA model. Instead, they are used to assess whether governance cognition and implementation capacity add information beyond the core institutional arrangements (Figure 1).

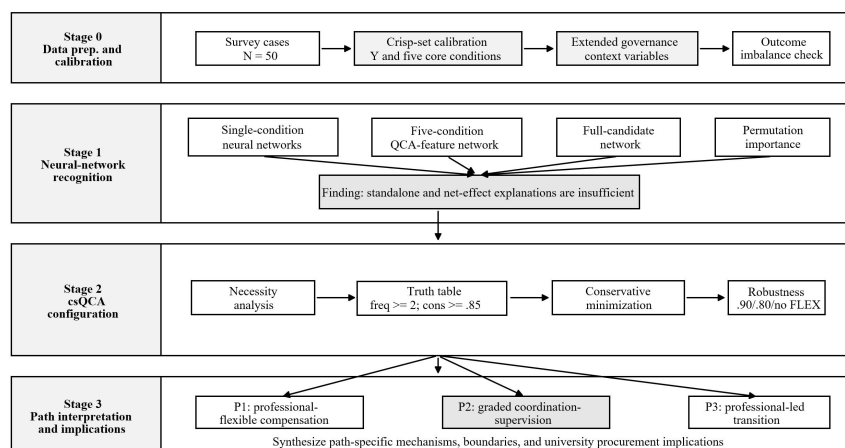


Figure 1 Analytical Workflow Linking Neural-Network Nonlinear Recognition and csQCA

3 RESEARCH DESIGN

3.1 Data and Case Unit

The questionnaire was distributed through university procurement-related work groups in September 2024, yielding 50 valid responses. Respondents include procurement department heads and staff, demand department heads and staff, financial personnel, oversight actors, and evaluation experts. The case unit is the individual respondent observation rather than a uniquely identified university. Because the survey did not collect school names or institutional identifiers, it is impossible to determine whether multiple respondents came from the same university. The analysis is therefore

positioned as an exploratory configurational study of reported institutional arrangements and role-based satisfaction (Table 1).

Table 1 Sample Structure (N = 50)

Dimension	Category	n	%
University type	Ministry-affiliated university	33	66.0
University type	Municipal university	8	16.0
University type	Central university	5	10.0
University type	Other	4	8.0
Role	Procurement department head/staff	33	66.0
Role	Demand department head/staff	13	26.0
Role	Finance, oversight, evaluation expert, or other	4	8.0
Tenure	Five years or less	31	62.0
Tenure	Six to ten years	10	20.0
Tenure	Eleven years or more	9	18.0

3.2 Calibration

The outcome Y denotes procurement satisfaction improvement. Cases selecting “some improvement” or “substantial improvement” are calibrated as 1; cases selecting “no significant change” are calibrated as 0. This calibration captures whether improvement occurred, not the intensity of improvement. Because only seven cases report substantial improvement, a separate high-improvement truth-table analysis would be underpowered. The calibration rules for the outcome and five core conditions are shown in Table 2.

Table 2 Variable Definition and Crisp-Set Calibration

Variable	Set meaning	Calibration rule	1/0 cases
Y	Improved procurement satisfaction	1 = some or substantial improvement; 0 = no significant change	41/9
GRADE	Presence of graded review rules	1 = review differentiated by amount, complexity, or project type; 0 = no graded review	27/23
COORD	Procurement-demand coordination	1 = procurement and demand departments jointly participate; 0 = otherwise	26/24
PROF	Professional support	1 = experts, third parties, or professional committees participate; 0 = otherwise	35/15
SUP	Financial/audit supervision	1 = finance, audit, or oversight actors participate; 0 = otherwise	33/17
FLEX	Flexible review arrangements	1 = countersignature, online, correspondence, third-party, or hybrid review; 0 = otherwise	19/31

3.3 Neural-Network Nonlinear Recognition

The neural-network stage is used to identify nonlinear explanatory signals before QCA [12, 18]. Three groups of models are estimated. First, single-condition models examine whether any one condition can distinguish satisfaction improvement on its own. Second, a five-condition model includes only the conditions used in the subsequent QCA: GRADE, COORD, PROF, SUP, and FLEX. Third, a full-candidate model adds dedicated rules, procedural response, review-team scale, goal understanding, meeting-based review, and whole-process cognition. A single-hidden-layer weighted backpropagation neural network is used. Because positive cases account for 82% of the sample, balanced accuracy and AUC are emphasized rather than raw accuracy [19]. Permutation importance is used to assess the relative contribution of candidate conditions [20].

3.4 csQCA Procedure and Thresholds

After neural-network recognition indicates that standalone explanations are insufficient, csQCA is used to identify sufficient configurations. The procedure includes necessary-condition analysis, truth-table construction, conservative solution minimization, and robustness tests [12-13]. A consistency value of 0.90 is used as the conventional reference for necessary conditions. The main truth table uses a frequency threshold of 2, meaning that a retained truth-table row must include at least 4% of the sample. Because membership in the outcome set is 0.82, a sufficiency threshold of 0.80 would be lower than the outcome base rate; the main model therefore uses a raw-consistency threshold of 0.85 and is checked at 0.90. To avoid unsupported assumptions under limited diversity, Boolean minimization does not use logical remainders and reports conservative solutions [21-22].

4 RESULTS

4.1 Descriptive Evidence

Among the 50 respondents, 34 report “some improvement” and 7 report “substantial improvement”; together, 41 respondents, or 82%, report improved procurement satisfaction. Nine respondents, or 18%, report no significant change. This distribution indicates that positive implementation feedback is widespread, but it does not imply a strong objective performance leap because only 14% report substantial improvement. Among the five core conditions, professional support is most prevalent at 70%, followed by financial/audit supervision at 66%, graded review rules at 54%, procurement-demand coordination at 52%, and flexible review arrangements at 38%. These proportions describe condition distribution, not causal sufficiency.

The outcome distribution has two implications. First, most respondents perceive at least some positive change after demand-management rules were implemented. Second, the relatively small number of non-improved cases makes raw accuracy misleading. A model that predicts all cases as improved would reach 82% accuracy but would have no capacity to identify non-improved cases. For this reason, the neural-network stage emphasizes balanced accuracy, specificity, and AUC.

Between outcome groups, procurement-demand coordination, flexible review arrangements, complete goal understanding, and review-team scale are more prevalent among improved cases. Complete goal understanding is present in 61.0% of improved cases and 33.3% of non-improved cases. Review-team scale is present in 48.8% and 22.2%, respectively, while procurement-demand coordination is present in 56.1% and 33.3%, respectively. These differences suggest that satisfaction improvement is related not only to the presence of formal rules but also to whether policy goals are understood, whether the review organization has sufficient capacity, and whether procurement and demand departments jointly review requirements.

Professional support is present in 70.7% of improved cases and 66.7% of non-improved cases. Procedural response is present in 95.1% of improved cases and in all non-improved cases. This pattern shows that the presence of procedures or experts cannot be equated with satisfaction improvement. Financial/audit supervision is more prevalent among non-improved cases than improved cases, which does not mean supervision reduces satisfaction. It more plausibly suggests that supervision becomes positively experienced only when combined with graded rules and coordination; without such complementary conditions, supervision may be perceived primarily as an additional constraint (Figure 2).

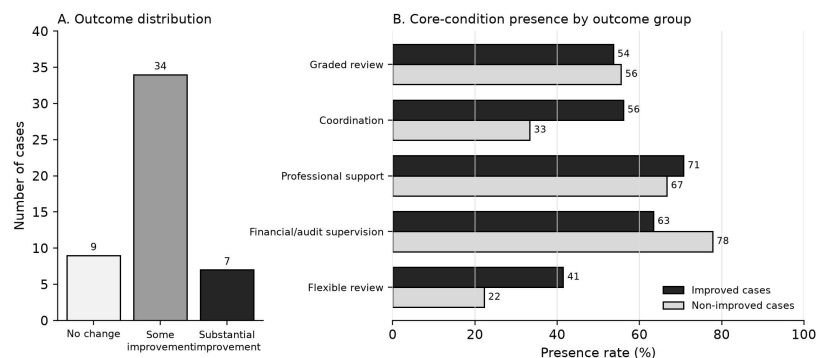


Figure 2 Outcome Distribution and Core-Condition Presence by Outcome Group

4.2 Neural-Network Nonlinear Recognition

The neural-network results first show that single conditions cannot reliably distinguish whether procurement satisfaction improves. The mean balanced accuracy of the single-condition models is 0.544, and the maximum is 0.638. The highest-ranking single conditions are complete goal understanding, meeting-based review, review-team scale, procurement-demand coordination, and whole-process cognition, but their AUC values remain below 0.60. No single condition therefore provides a stable standalone explanation.

Model-level comparisons lead to the same conclusion. The all-improved baseline reaches an accuracy of 0.820 because improved cases dominate the sample, but its specificity is 0 and it cannot identify non-improved cases. The five-condition QCA-feature network records a balanced accuracy of 0.470 and an AUC of 0.485, indicating weak predictive performance when the five core conditions are treated as a conventional feature set. The full-candidate model improves to a balanced accuracy of 0.564 and an AUC of 0.620. This improvement is meaningful but still modest. It indicates that extended governance-context variables add information, while also showing that the outcome is better understood as a configurational phenomenon than as a strong prediction task.

Figure 3 shows that complete goal understanding is the strongest single condition, with balanced accuracy of 0.638. Meeting-based review and review-team scale each reach 0.633, procurement-demand coordination reaches 0.614, and whole-process cognition reaches 0.612. Although these values exceed the random benchmark of 0.50, their AUC values hover around 0.55. Single conditions thus provide useful signals but cannot carry the main explanatory burden.

The single-condition results also reveal why QCA is needed. Graded review rules and professional support are not always strong standalone predictors, yet they occupy important positions in the QCA paths. Their effects are therefore

not primarily independent predictive effects. They operate as contextual functions when combined with other conditions. For example, graded review rules combine with professional support and flexible review in P1 and with coordination and supervision in P2; professional support functions as knowledge supplementation in P1 and as a transitional substitute in P3 (Table 3, Figure 4).

Permutation importance shows that whole-process cognition, procurement-demand coordination, complete goal understanding, graded review rules, and review-team scale contribute most to the full-candidate network, whereas procedural response contributes almost no discriminating information. This finding is consistent with the subsequent QCA results: formal procedures alone do not explain satisfaction improvement; the key question is how rules, coordination, cognition, and organizational capacity are combined.

Table 3 Neural-Network Nonlinear Recognition Results

Model	Input conditions	Accuracy	Balanced accuracy	AUC	Interpretation
All-improved baseline	Majority-class prediction only	0.820	0.500	0.500	Cannot identify non-improved cases
Single-condition models	Each of 11 candidate conditions separately	-	0.544	-	Standalone explanation is weak
Best single condition	Complete goal understanding	0.620	0.638	0.544	Still insufficient as a stable explanation
Five-condition model	GRADE, COORD, PROF, SUP, FLEX	0.549	0.470	0.485	Core conditions are better treated configurationally
Full-candidate model	Core conditions plus governance-context variables	0.664	0.564	0.620	Limited nonlinear information gain

Note: The single-condition result reports the mean of eleven models, each estimated with one candidate condition. Balanced accuracy is reported to address the positive-outcome imbalance.

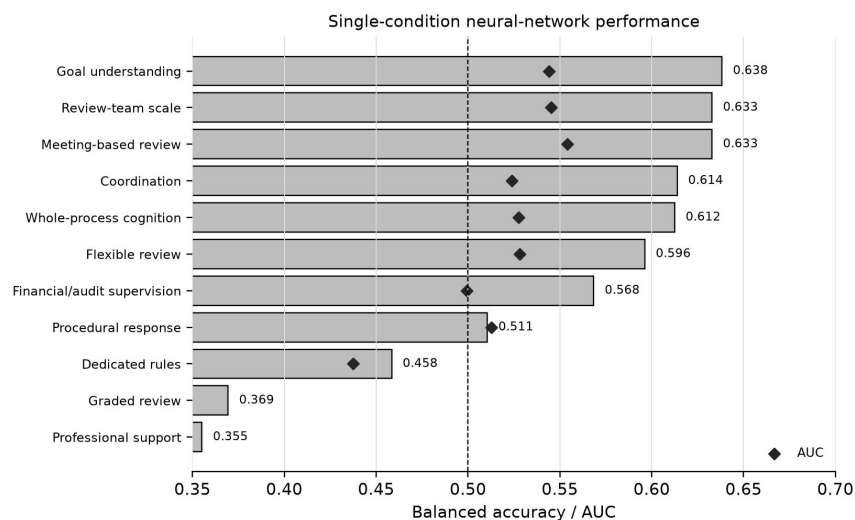


Figure 3 Balanced Accuracy and AUC of Single-Condition Neural-Network Models

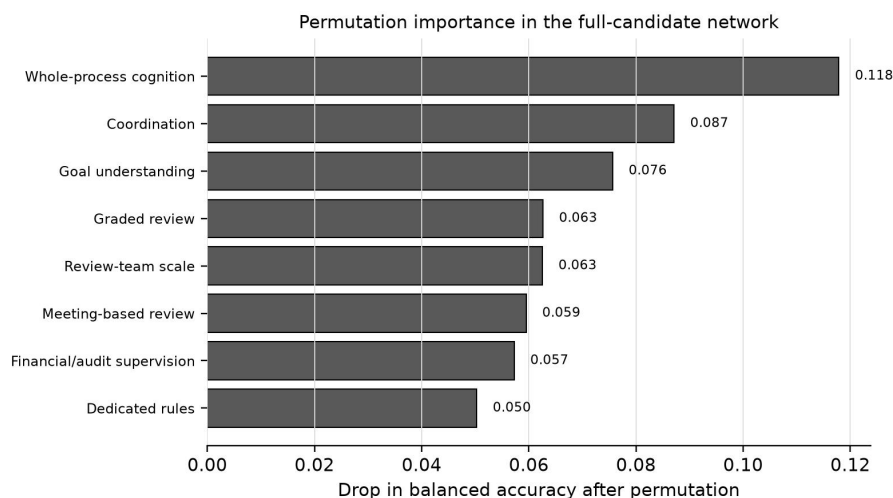


Figure 4 Permutation Importance of Candidate Conditions in the Full-Candidate Neural Network

Figure 5 further explains the configurational structure. Procurement-demand coordination is positively correlated with financial/audit supervision, suggesting that in some universities coordination and supervision appear together, consistent with the structure of P2. Flexible review arrangements are strongly negatively correlated with meeting-based review, indicating that the two are not merely different labels for the same review mode but represent substitutive arrangements. Graded review rules are negatively correlated with whole-process cognition, suggesting that some respondents may recognize the importance of whole-process responsibility even when their organizations have not yet established clear graded rules. This cautions against equating cognition with institutional maturity.

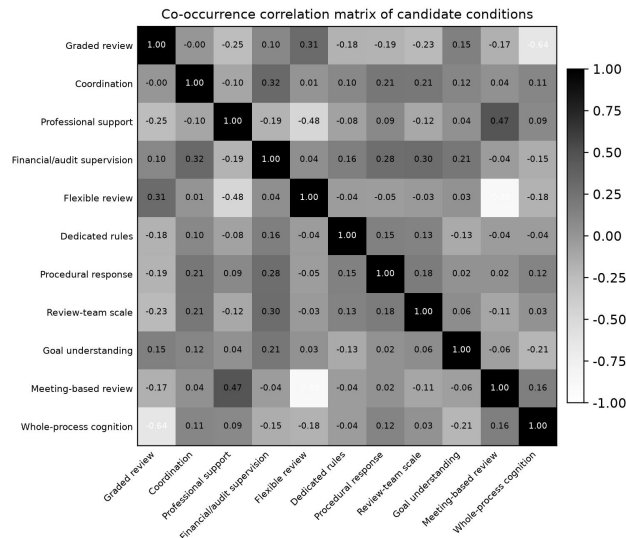


Figure 5 Co-Occurrence Correlation Matrix of Candidate Conditions

4.3 Necessary-Condition Analysis

Table 4 Necessary-Condition Test

Condition	Necessity consistency	Necessity coverage	X=1, Y=1 cases
Graded review rules	0.537	0.815	22
Procurement-demand coordination	0.561	0.885	23
Professional support	0.707	0.829	29
Financial/audit supervision	0.634	0.788	26
Flexible review arrangements	0.415	0.895	17
Procedural response	0.951	0.812	39

Note: The conventional reference threshold for necessary-condition consistency is 0.90. PROC has high consistency, but because it is present in 48 of 50 cases, its coverage and discriminating power are limited.

The necessity consistency of all five core conditions is below 0.90 (Table 4), indicating that improved satisfaction does not require any one core condition to be present on its own. The consistency of procedural response is 0.951, but this condition is almost universally present and therefore cannot explain why some respondents report improvement while others do not. Necessary-condition analysis and neural-network recognition thus point to the same conclusion: satisfaction improvement is not determined by a single rule or review arrangement.

4.4 Truth Table and Sufficient Configurations

Table 5 Positive Truth-Table Rows Included in Boolean Minimization

GRADE	COORD	PROF	SUP	FLEX	Cases	Y=1	Consistency
1	1	1	1	0	5	5	1.000
0	0	1	0	0	3	3	1.000
0	1	1	0	0	3	3	1.000
1	0	1	0	1	2	2	1.000
1	0	1	1	1	2	2	1.000
1	1	0	1	0	2	2	1.000

The three paths all have consistency of 1.000, meaning that under the current sample and threshold settings all cases falling into these paths belong to the improved-satisfaction outcome. The overall coverage is 0.415: the main solution covers 17 of the 41 improved cases, while 24 improved cases remain outside the conservative solution. This does not indicate model failure. Because the analysis avoids logical remainders and uses both frequency and consistency thresholds, the solution should be interpreted as a conservative set of core paths rather than an attempt to cover all positive cases.

P1 is the professional-flexible compensation path (GRADE*~COORD*PROF*FLEX). In the presence of graded review rules, professional support and flexible review arrangements are associated with improved satisfaction even when procurement and demand departments do not jointly participate in the review group. This path indicates that external or professional knowledge and procedural flexibility can partly compensate for insufficient departmental coordination. However, P1 covers only four improved cases, with raw coverage of 9.8%, and should not be generalized as a universal model. Its boundary is clear: professional support and flexible review must be constrained by graded rules; otherwise, expert advice may become fragmented and flexible review may blur responsibility (Table 5-6, Figure 6-7).

Table 6 Configurational Paths Associated with Improved Procurement Satisfaction

Condition	P1 Professional-flexible compensation	P2 Graded coordination-supervision	P3 Professional-led transition
Graded review rules (GRADE)	●	●	□
Procurement-demand coordination (COORD)	□	●	○
Professional support (PROF)	●	○	●
Financial/audit supervision (SUP)	○	●	□
Flexible review arrangements (FLEX)	●	□	□
Consistency	1.000	1.000	1.000
Raw coverage	0.098	0.171	0.146
Unique coverage	0.098	0.171	0.146
Typical improved cases	4	7	6

Note: ● = condition present; □ = condition absent; ○ = condition not restricted in the path expression. Overall solution consistency = 1.000; overall solution coverage = 0.415.

Path	GRADE	COORD	PROF	SUP	FLEX	Mechanism
P1 professional-flexible compensation	●	□	●	○	●	Expertise and flexible review compensate for weak coordination
P2 graded coordination-supervision	●	●	○	●	□	Rules, coordination, and supervision form an integrated governance bundle
P3 professional-led transition	□	○	●	□	□	Professional support generates transitional improvement under weak institutionalization

Note: ● = condition present; □ = condition absent; ○ = condition not restricted in the path expression.

Figure 6 csQCA Path Structure for Improved Procurement Satisfaction

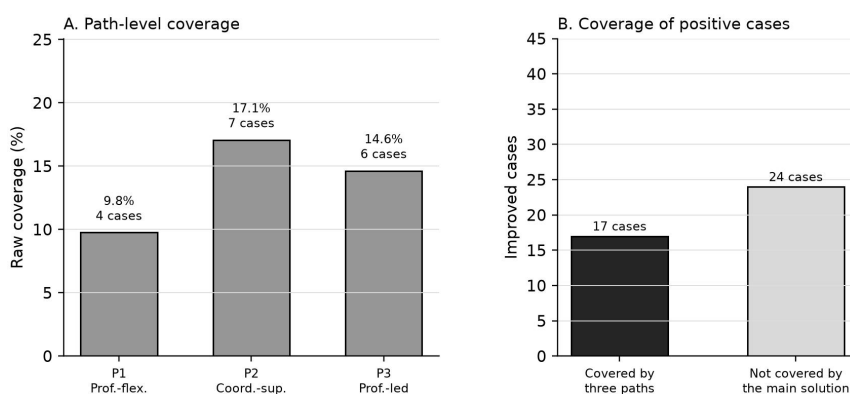


Figure 7 Path Coverage Contribution and Coverage of Positive Cases

P2 is the graded coordination-supervision path (GRADE*COORD*SUP*~FLEX). When graded rules, procurement-demand coordination, and financial/audit supervision coexist, improved satisfaction appears even if the review mode is not primarily countersignature, online, or hybrid review. P2 covers seven improved cases and has the highest raw coverage among the three paths at 17.1%. It represents a relatively institutionalized governance bundle: graded rules allocate review intensity, coordination reduces translation loss between technical and procurement language, and supervision embeds budgetary and accountability constraints at the front end.

P3 is the professional-led transition path (~GRADE*PROF*~SUP*~FLEX). When graded rules, financial/audit supervision, and flexible review arrangements are absent, professional support is still associated with six improved cases. This path shows that professional knowledge can improve requirement expression, technical judgment, and market recognition. Yet it should be viewed as transitional rather than mature. If universities rely on experts or third parties without building graded rules and supervision mechanisms, they may obtain short-term improvement in complex projects but fail to develop replicable and accountable institutional capacity.

4.5 Robustness and Boundary Sensitivity

Raising the consistency threshold from 0.85 to 0.90 leaves the three main paths and overall indicators unchanged (Table 7). Removing FLEX retains the substitutive role of professional support and the complementarity between graded rules, coordination, and supervision. Lowering the threshold to 0.80 adds the path $\text{GRADE}^*\text{COORD}^*\sim\text{PROF}^*\text{SUP}$. Because 0.80 is below the outcome base rate of 0.82 and the added path disappears when the threshold is raised, this path is treated as a boundary phenomenon rather than a core explanation.

Table 7 Robustness and Sensitivity Tests

Test	Setting	Solution structure	Solution consistency	Solution coverage
Main model	Five conditions; threshold .85	P1, P2, P3	1.000	0.415
Strict threshold	Five conditions; threshold .90	P1, P2, P3	1.000	0.415
Four-condition model	FLEX removed; threshold .85	$\sim\text{GRADE}^*\text{PROF}^*\sim\text{SUP}$; $\text{GRADE}^*\text{PROF}^*\text{SUP}$; $\text{GRADE}^*\text{COORD}^*\text{SUP}$	0.957	0.537
Boundary test	Five conditions; threshold .80	P1, P2, P3, and $\text{GRADE}^*\text{COORD}^*\sim\text{PROF}^*\text{SUP}$	0.955	0.512

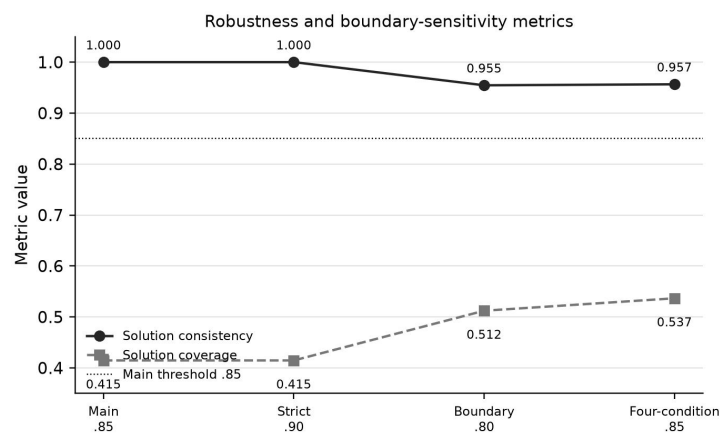


Figure 8 Robustness and Boundary-Sensitivity Metrics

Figure 8 visualizes the robustness logic. The main and strict-threshold models have identical consistency and coverage, indicating that the three paths are not accidental products of the 0.85 threshold. The boundary-threshold and four-condition models increase coverage but reduce consistency to 0.955 and 0.957. Thus, a more expansive solution would explain more cases but with lower precision. In line with management research's emphasis on robust interpretation, the analysis retains the three higher-consistency paths as the core solution.

5 DISCUSSION

5.1 From Nonlinear Recognition to Configurational Explanation

The neural-network stage clarifies why configurational explanation is necessary. The mean balanced accuracy of single-condition models is only 0.544, and the five-condition model does not produce stable predictive performance. Satisfaction improvement is therefore not a direct consequence of any one condition. The limited improvement of the full-candidate model further indicates that governance cognition, goal understanding, and organizational capacity matter, but they do not transform the problem into a strong prediction task. QCA is therefore not a decorative second method; it is the appropriate explanatory step after the neural network reveals nonlinear and combinational structure.

Methodologically, a single-variable proportion comparison might encourage linear statements such as "coordination is better" or "expert participation is better." Yet the descriptive figures show that several conditions differ little across outcome groups, while the co-occurrence matrix reveals substitutive and complementary relationships. Practically, university procurement reform is often understood as the improvement of texts, the addition of review actors, or the expansion of procedures. The results suggest that such measures matter only when embedded in a suitable bundle. The question is not simply whether a measure exists, but what function it performs in a particular configuration.

5.2 P1: Using Expertise and Procedural Flexibility to Compensate for Weak Coordination

P1 is most relevant to projects with high professional complexity and weak cross-departmental coordination. In research equipment, laboratory platforms, information systems, and specialized services, demand departments understand use scenarios and technical objectives, whereas procurement departments understand procedures and market rules. If all actors must coordinate through fixed meetings, the review burden may increase. Expert argumentation, third-party

consultation, online countersignature, or hybrid review can improve demand text quality without relying entirely on mature departmental coordination.

Nevertheless, P1 contains clear risks. Professional support can be misused as responsibility outsourcing, leaving the purchaser with only a formal review role. Flexible review can reduce face-to-face clarification, leaving disagreements unresolved. If graded rules are unclear, ordinary projects may be over-reviewed and complex projects may be under-reviewed. P1 should therefore be understood as a compensatory configuration for universities that have some classification awareness and professional resources but have not yet established stable coordination mechanisms.

5.3 P2: A Main Institutional Path for University Demand Management

P2 has the clearest institutional implications. It addresses three core tensions in procurement demand management. The tension between project heterogeneity and limited review resources is handled by graded review rules. The tension between technical objectives and procurement rules is handled by procurement-demand coordination. The tension between business needs and budgetary compliance is handled by financial/audit supervision. This path explains why some universities can obtain positive satisfaction feedback even when they rely on relatively conventional review modes rather than flexible or online review.

P2 also represents a shift from document-centered review to front-end cross-departmental governance. Procurement departments are not merely responsible for issuing procurement documents; demand departments are not merely responsible for submitting applications; and financial or oversight actors are not merely responsible for ex post inspection. When these actors enter the front end under clear graded rules, requirement formation, procurement implementation, contract clauses, and later acceptance can be connected in a traceable accountability chain. P2 is therefore the path most likely to become a durable institutional capability.

5.4 P3: Professional Support as Effective but Transitional

P3 demonstrates the practical value of professional support under weak institutionalization. Some universities may not yet have mature graded rules or embedded supervision, but expert or third-party participation can still improve technical parameters, market investigation, and communication between demand and procurement departments. Front-line actors may perceive this improvement quickly because it reduces repeated revisions, supplier challenges, or failed procurement attempts.

However, P3 cannot be interpreted as “experts are enough.” Professional support solves knowledge problems but does not fully solve resource-allocation, accountability, or compliance problems. Without graded rules, it is uncertain when professional support should be triggered and how advice should be adopted. Without financial/audit supervision, technical requirements may become disconnected from budgets, asset allocation, and later performance capacity. Without a stable review mechanism, professional advice may remain case-specific rather than becoming organizational learning. Universities following P3 should therefore treat professional support as an entry point for capability building.

5.5 Boundary Conditions Revealed by Extended Variables

The neural-network importance results show that whole-process cognition, complete goal understanding, and review-team scale are salient. These variables help explain why the main QCA solution has moderate coverage. Satisfaction improvement depends not only on whether institutional arrangements exist but also on whether actors understand demand management as a chain connecting investigation, procurement implementation, contract formation, and performance acceptance, and whether the review team has the organizational capacity to integrate diverse information.

Whole-process cognition requires careful interpretation. Its importance ranking does not mean that it has a simple positive association with satisfaction improvement. The extended statistics show that it is more prevalent among non-improved cases. A plausible explanation is that respondents with stronger whole-process cognition may also have higher expectations and may more easily identify implementation deficiencies. This finding suggests that future research should distinguish between recognizing the importance of demand management and having the organizational capacity to implement it.

Complete goal understanding and review-team scale more directly reflect implementation capacity. Goal understanding turns abstract compliance requirements into concrete review criteria, preventing demand management from becoming purely formal. Review-team scale indicates whether the organization can accommodate procurement, demand, finance, oversight, and professional knowledge. A small team may lack information diversity; a large team without clear rules may create coordination costs. The neural-network results therefore indicate that path effectiveness depends on the cognitive and organizational basis through which configurations are implemented.

6 MANAGERIAL IMPLICATIONS

6.1 Build P2 as the Routine Path: Graded Rules, Coordination, and Supervision

For universities with relatively complete internal functions, P2 should be prioritized. Universities should establish a project classification list based on budget amount, technical complexity, information-system attributes, single-source

risk, and market uncertainty. They should also define a coordination responsibility list: demand departments specify functions and use scenarios; procurement departments review procurement method, evaluation criteria, and contract compliance; financial or asset departments review budget sources and asset consistency; and oversight actors identify integrity and procedural risks. Finally, universities should maintain traceable records of market investigation, requirement argumentation, parameter revision, review opinions, and the adoption or rejection of such opinions. Operationally, P2 should not become another approval layer. It should be embedded at the front end of procurement. High-risk projects can use joint pre-review before the procurement application is formally submitted, while low- and medium-risk projects can use checklist-based verification to avoid over-review. Financial and audit actors should act not only as veto players but as providers of boundaries: budget constraints, asset standards, internal-control requirements, and common violation risks should be communicated early.

6.2 Use P1 as a Compensatory Path Where Coordination Is Weak

Universities with weak cross-departmental coordination but some classification awareness can use P1 as an improvement starting point. Complex technical projects can introduce industry experts, third-party organizations, or internal professional committees. Standardized projects that require confirmation by several actors can use online countersignature, correspondence review, or hybrid review to reduce meeting costs. Flexibility must be institutionalized: universities should specify which projects can be reviewed online, which require meetings, and which can be simplified after third-party argumentation.

P1 should also serve coordination capacity building rather than bypass coordination. Expert opinions can be converted into learning materials for demand and procurement departments: which parameters may be discriminatory, which requirement expressions affect competition, which technical indicators should be expressed as functions, and which contract clauses are linked to performance risks. In this way, professional support solves the current project problem while improving internal capability.

6.3 Transform P3 from Expert Dependence into Institutional Capability

Universities following P3 should treat professional support as a transitional mechanism. They should build a professional-support ledger that records not only experts and review dates, but also the requirement problems addressed, the adoption of expert opinions, reasons for non-adoption, subsequent procurement results, and performance feedback. After several projects, common problems can be translated into category-specific templates, negative lists, or review prompts. For example, information-system projects may require templates for data interfaces, cybersecurity, maintenance services, and acceptance indicators; equipment projects may require templates for core parameters, compatibility, after-sales service, and consumable costs.

Financial and audit supervision should be embedded gradually. Universities without stable supervision mechanisms can first pilot financial/audit participation in high-budget, technically complex, or high-performance-risk projects and then expand it to key categories. Oversight actors need not participate in every technical detail; they should focus on budget reasonableness, asset allocation consistency, procurement method risks, payment arrangements, and performance-acceptance responsibilities.

6.4 Incorporate Extended Variables into the Improvement Cycle

Training should be differentiated by role. Demand departments need to learn how to translate use needs into competitive, verifiable, and performable procurement requirements. Procurement departments need to improve their ability to identify unreasonable technical requirements and market-competition risks. Financial and oversight actors need to understand the efficiency costs of excessive constraints. Experts and third-party organizations need to recognize that their advice supports, rather than replaces, purchaser responsibility. Only when actors share a common understanding of demand-management goals can coordination move beyond formal participation.

Review-team scale should also match project complexity. Ordinary projects may use simplified review by procurement and demand departments. Complex projects should add professional, financial, asset, information-technology, or oversight members. Disputed projects may introduce external experts or third-party organizations. As the number of participants increases, universities should clearly designate the chair, opinion consolidator, revision owner, and final confirmer to prevent a situation in which many actors participate but no actor takes responsibility.

6.5 Evaluate Configurations Rather than Isolated Measures

Internal evaluation should not ask only whether a university has formulated rules, uses online review, or introduces experts. It should record which path is used for each project and compare cycle time, number of requirement revisions, number of effective competing suppliers, supplier challenges or complaints, contract changes, acceptance problems, and role-based satisfaction. If P1 projects have short cycles but many later contract changes, flexible review may be sacrificing front-end argumentation depth. If P2 projects take longer but have fewer complaints and performance problems, the costs of coordination and supervision may be justified by governance benefits. If P3 projects rely on experts without rule accumulation, they should be transformed toward P1 or P2.

Finally, satisfaction evaluation should be distinguished from objective performance evaluation. Satisfaction improvement reflects role experience and policy acceptance, both of which are important for sustaining reform. Yet satisfaction alone cannot prove comprehensive procurement performance improvement. Universities should evaluate satisfaction, efficiency, competition adequacy, budget execution, contract performance, and acceptance quality together. The path results of this study provide a starting framework for identifying the advantages, costs, and boundaries of different governance bundles.

7 CONCLUSION AND LIMITATIONS

This study examines which configurations of procurement demand-management conditions are associated with improved university procurement satisfaction. Neural-network-based nonlinear recognition shows that single conditions and the five core conditions have limited standalone explanatory capacity, while the inclusion of whole-process cognition, goal understanding, review-team scale, and other contextual variables improves model performance modestly. This supports the turn toward configurational explanation. csQCA identifies three paths: professional-flexible compensation, graded coordination-supervision, and professional-led transition. The findings suggest that university procurement demand-management reform should move from asking how many controls have been added to asking what matched governance bundle has been constructed.

The study has limitations. First, the sample contains 50 valid responses obtained through work groups rather than probability sampling. The neural-network results should therefore be interpreted as nonlinear recognition rather than as a stable predictive model. Second, because the survey lacks unique university identifiers, cases cannot be strictly equated with institutions. Third, the outcome is subjective satisfaction improvement, and positive outcomes account for 82% of the sample, producing outcome imbalance and information compression. Fourth, conditions and outcome are measured in the same questionnaire, raising the possibility of common-method bias and preventing strong temporal-causal claims. Future research should identify universities as explicit case units, match institutional documents and procurement project records, and include objective indicators such as procurement cycle time, competition level, contract performance, and acceptance quality. Such work can further distinguish the configurations that improve subjective acceptance from those that improve objective procurement performance.

COMPETING INTERESTS

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