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Hierarchical Capability Stratification with Entropy-Weighted TOPSIS and Coupling Coordination Analysis for Heterogeneous Distributed Networks

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Abstract: Heterogeneous edge computing networks with spatially distributed nodes face persistent capability assessment challenges when node performance depends on multiple non-additive dimensions and inter-subsystem coupling. This paper develops a four-component framework for stratified capability evaluation across 16 distributed nodes characterized by a 5-dimensional capability vector spanning computational, digital, sustainability, infrastructure, and expertise dimensions. The Entropy-Weighted TOPSIS composite indexing module produces a Composite Capability Index that reveals a strongly unbalanced spatial distribution following a single-hub-leading, middle-tier-fragmentation, and tail-cluster-aggregation topology, with the overall mean at 0.32 and the dominant hub reaching 0.78. The regression analysis module quantifies capability impact on system performance, confirming a positive empowerment effect of 0.72 ($p < 0.001$) concentrated on openness and coordination dimensions while remaining weak on innovation, sustainability, and shared-access dimensions. The Coupling Coordination Degree model identifies that 65% of nodes exhibit mild dyscoordination with the coupling index averaging 0.45 across the panel, while edge-region nodes follow a distinct low-capability-high-openness-high-performance trajectory absent from core nodes. Heterogeneity testing confirms statistically significant capability-performance gaps between edge and core regions and between hub and peripheral clusters under leave-one-out validation. The integrated framework supports adaptive resource allocation for distributed systems requiring fine-grained capability stratification.

1. Introduction

Distributed systems with spatially heterogeneous nodes fail to produce uniform performance even under identical control policies. The reason has been understood for some time: capability varies across nodes along orthogonal dimensions that no single metric can summarize. The harder

question is how to score that capability in a way that survives ablation, ranks the same way under reasonable weight perturbations, and admits clean impact analysis downstream. Single-metric benchmarks miss the trade-offs that operators actually face; pooled aggregate scores hide the spatial concentration that dominates the deployment problem [1,2]. Recent capability assessment frameworks in heterogeneous edge computing have moved toward explicit multi-dimensional scoring with transparent weight construction [3,4]. The harder cases involve panels where the dominant hub concentrates most of the high-end capability, the middle tier fractures into disconnected sub-clusters, and the tail aggregates around floor values that no policy lever lifts cheaply. Identifying that topology before scheduling resources separates capability-aware deployment from uniform-policy deployment that wastes effort on tail nodes and under-allocates to middle-tier nodes that would respond [5,6].

Entropy-weighted TOPSIS has displaced subjective weighting in nearly every published composite-indicator pipeline because objective weight derivation through entropy of the empirical column distribution removes the analyst-bias degree of freedom that subjective weighting introduces [7,8]. The recipe is mechanical: normalize each capability dimension to the [0,1] interval, derive column entropies as inverse-variance weights, compute distance to ideal and anti-ideal solutions in the weighted space, and rank by relative closeness. The trade-off is that entropy weighting fixes the weight as a function of the data and cannot incorporate prior domain knowledge that some dimensions deserve more emphasis on principle. Recent extensions handle this by mixing entropy-derived weights with subjective Delphi or AHP-derived priors under a hybrid scheme, but the empirical gain over pure entropy weighting remains modest in panels with informative variance [9,10]. The deeper challenge is dimensional consistency. When the five constituent capability dimensions are themselves composite indices derived from heterogeneous raw indicators, the entropy step on the constituent layer interacts with the entropy step on the composite layer in ways that the standard derivation does not analyze [11,12].

Once composite capability is scored, the next stage quantifies its impact on system performance, and recent work has moved past simple OLS into explicit heterogeneous treatment effect estimation. Double machine learning and orthogonal score methods are now standard for panel regression under high-dimensional confounding, and the empirical literature on distributed systems performance has caught up to the methodological frontier in the last three years [13,14]. The heterogeneity-aware estimation problem becomes acute when the unit-level treatment effect varies systematically with capability tier, because pooled estimators average over the cross-section and report a treatment effect that no individual tier actually experiences. Tier-stratified estimators handle this through interaction terms or split-sample analysis, and the choice between the two is governed by sample-size considerations rather than asymptotic preference [15,16]. What is missing in most published applications is a clean handoff between the composite-indexing stage and the regression stage that propagates the indexing uncertainty into the regression standard errors. Without that handoff, the reported impact estimates are conditional on a point estimate of capability that no longer admits its own confidence region [17,18].

The final piece is system coupling. Capability and performance can co-vary positively while their joint distribution exhibits structural mis-alignment, and detecting this requires explicit coupling-coordination analysis rather than correlation analysis alone. The coupling coordination degree model decomposes the joint distribution into a coupling component that measures the strength of the linkage and a coordination component that measures whether the two systems develop in step or at different rates [19,20]. Heterogeneity testing on top of this provides the formal apparatus for asking whether coupling strength varies systematically across node clusters, which is the production question that motivates any tier-aware deployment policy [21,22]. We integrate four components into a single pipeline: entropy-weighted TOPSIS composite indexing on a 5-

dimensional capability vector, regression analysis with stratified treatment-effect estimation, coupling coordination degree modeling at the panel level, and heterogeneity testing for inter-cluster comparison. The pipeline is validated on a 16-node distributed network with documented dimensional measurements, and the spatial topology recovered from the indexing stage drives all downstream analysis [23,24].

2. Methodology

2.1. Entropy-Weighted TOPSIS Composite Indexing

Composite indexing on a 5-dimensional capability vector is the first task. Each node carries measurements on computational, digital, sustainability, infrastructure, and expertise dimensions that vary by orders of magnitude in their natural scales, and the indexing step must produce a single scalar score that survives ablation, ranks consistently under reasonable weight perturbations, and admits clean uncertainty propagation to the next stage. Two design decisions govern the construction [25, 26]. The first concerns weight derivation. A subjective scheme (Delphi, AHP, expert consensus) places analyst priors into the score and makes the resulting index reflect prior beliefs about which dimensions matter; an objective scheme uses data variance to assign weights and makes the score depend only on the empirical distribution. We adopt the objective route for the same reason that information-criterion model selection has displaced subjective penalty terms in time-series regression: the variance signal is observable, the analyst's prior is not, and reviewers can audit the weight construction without re-running the assessment under different priors.For each dimension j we first column-normalize the raw indicator vector to remove scale heterogeneity across dimensions, then compute the column entropy. Entropy is high when the per-node values are uniformly distributed (the dimension does not distinguish nodes) and low when the distribution is concentrated (the dimension separates strong nodes from weak nodes cleanly). Inverting and renormalizing gives the entropy weight:

$$e_j = -\frac{1}{\ln n}\sum_{i=1}^{n} p_{ij}\ln p_{ij}, \quad p_{ij} = \frac{\tilde{r}_{ij}}{\sum_{i=1}^{n}\tilde{r}_{ij}}, \quad w_j = \frac{1-e_j}{\sum_{k=1}^{m}(1-e_k)} \tag{1}$$

The 1/ln(n) factor normalizes entropy to [0, 1] regardless of node count, so the same weight derivation applies across panels of different sizes. The resulting weight is high for dimensions that discriminate nodes sharply and low for dimensions where node values cluster around a common level. The second design decision is how to aggregate the weighted dimensions into a single score. Linear weighted sum is the obvious choice but discards information about each node's position relative to the panel envelope. TOPSIS recovers that information by computing distance to a positive ideal (the column-wise maximum) and to a negative ideal (the column-wise minimum) in the weighted Euclidean space, then reporting the relative closeness:

$$S_i = \frac{D_i^-}{D_i^+ + D_i^-}, \quad D_i^{\pm} = \sqrt{\sum_{j=1}^{m} w_j\left(\tilde{r}_{ij} - r_j^{\pm}\right)^2} \tag{2}$$

$S_i \in [0, 1]$ takes the value 1 when the node sits exactly on the positive ideal and 0 when it sits on the negative ideal. Two nodes with the same weighted mean can have very different S values if one is balanced across all five dimensions and the other has a single dominant dimension compensating for a weak one. The S index penalizes the second pattern, which matters because reviewers of capability assessment frameworks routinely flag composite indices that reward dimensional concentration over balanced development. A practical concern is dimensional consistency between the constituent layer and the composite layer. The five capability dimensions are themselves

composite sub-indices derived from raw indicators. Running entropy weighting twice (once on raw indicators within each dimension, once on dimension scores at the composite level) can amplify or attenuate the discriminative signal depending on how raw-indicator variance propagates to the dimension layer. We handle this by computing the within-dimension entropy on min-max normalized raw indicators using the formula above, then aggregating to dimension scores using those within-dimension weights, then applying the dimension-level entropy weighting at the composite level. The two-layer derivation produces a single S value per node that admits clean interpretation and clean uncertainty propagation in the next stage.

2.2. Regression-Based Heterogeneous Empowerment Analysis

Capability scoring alone leaves the empowerment question open. The composite index S_i tells us where each node sits on the capability frontier, but it says nothing about whether capability translates into performance gain and whether the translation varies across nodes. A pooled OLS specification with S_i as the sole regressor would estimate a single empowerment coefficient β, but this would average over heterogeneous tier-specific effects and produce a number that no individual tier actually experiences. The production question is sharper: does the same capability increment translate into the same performance gain regardless of the node's baseline tier, or do strong-tier nodes capture disproportionate marginal returns from a unit increase in capability?

We answer this through a tier-stratified regression with interaction terms. Let $I_{ik} \in \{0, 1\}$ indicate whether node i belongs to tier k, with K = 3 tiers (weak, medium, strong) defined by tertile cuts on a separate capability proxy to avoid mechanical correlation with S_i itself. The regression is:

$$Y_i = \alpha + \beta S_i + \sum_{k=1}^{K-1} \gamma_k \left(S_i \cdot I_{ik} \right) + \mathbf{X}_i^{\top} \boldsymbol{\theta} + \epsilon_i \qquad (3)$$

Here β captures the baseline empowerment effect (the marginal performance gain from a unit increase in S_i for nodes in the omitted tier), γ_k captures the tier-k differential, and X is a vector of control variables including per-capita resource level, digital infrastructure penetration, and fiscal innovation expenditure. Including X handles confounders that would otherwise contaminate the empowerment estimate, and the choice of which controls to include is governed by the relevance criterion that each control has measured impact on Y_i independent of S_i in preliminary cross-validation.

Identification of β as a causal empowerment effect requires the standard exogeneity assumption that S_i is uncorrelated with ε_i conditional on X_i. This is plausible here because S_i is constructed from lagged capability indicators while Y_i is contemporaneous performance, so reverse causation through faster-than-period feedback is ruled out by construction. The within-period assumption that S_i does not pick up unobserved tier-specific shocks is checked through a placebo test on a randomly permuted tier assignment, and the placebo coefficient sits within the 95% confidence interval of zero in all 1000 permutation draws.

The heterogeneity test is the joint significance test on the γ vector. The Wald statistic is:

$$W = \boldsymbol{\gamma}^{\top} \left[\mathrm{Var}(\boldsymbol{\gamma}) \right]^{-1} \boldsymbol{\gamma} \xrightarrow{d} \chi^2_{K-1} \qquad (4)$$

Under the null H_0: $\gamma_1 = \gamma_2 = 0$, the empowerment effect is uniform across tiers and the interaction terms are statistically redundant. Rejection at conventional significance levels confirms that at least one tier experiences a differential effect, and the per-tier coefficient γ_k reports the direction and magnitude of that differential. We compute the variance matrix of γ using heteroscedasticity-robust HC3 standard errors, which is the small-sample correction appropriate for a 16-node panel where the asymptotic HC0 variance understates true sampling variation by roughly 15–20% in our

preliminary calibration.

Three diagnostics accompany the regression. The first is a leave-one-out sensitivity check that re-estimates β and the γ vector after dropping each node in turn, and reports the coefficient of variation across the 16 leave-one-out estimates. A coefficient of variation below 10% is the standard threshold for stability in small-panel regression analysis. The second is the placebo test on permuted tier assignments mentioned above. The third is a robustness check that re-estimates the model under alternative tier definitions (quartile cuts, quintile cuts, kernel-smoothed tier indicators) to confirm that the empowerment estimates do not depend on the specific tier discretization. All three diagnostics are reported in Section 3.

2.3. Coupling Coordination Degree Modeling and Cluster Heterogeneity Testing

Coupling coordination analysis closes a gap that regression alone leaves open. The regression in Section 2.B quantifies the marginal effect of capability on performance through a slope coefficient, but it treats capability and performance as separate variables linked by an unknown number. The more demanding question is whether capability and performance develop in coordinated balance across the panel or whether their joint distribution exhibits structural mis-alignment. Two nodes with the same composite capability S_i and the same performance Y_i can sit on very different points of the coupling distribution: one node may have high values on both axes through balanced development, the other may have a low-capability-high-performance profile that survives only because of compensating factors not captured by S_i.

The coupling degree C measures the strength of the linkage between the two systems through a normalized geometric-arithmetic ratio, while the coordination index T measures whether the two systems develop in step. The composite Coupling Coordination Degree D combines both into a single scalar:

$$C = \left[\frac{S \cdot Y}{\left((S+Y)/2\right)^2} \right]^{1/2}, \quad T = \mu S + \nu Y, \quad D = \sqrt{C \cdot T} \tag{5}$$

We adopt the symmetric weighting $\mu = \nu = 0.5$ because no prior empirical evidence justifies asymmetric emphasis on capability or performance, and the symmetric case admits the cleanest decomposition: D approaches 1 when both S and Y are high and proportionate, drops sharply when one of the two is near zero, and falls into intermediate values when both are moderate but the ratio between them deviates from unity. We classify the resulting D values into four tiers following the standard partition used in the coupling coordination literature: $D < 0.3$ indicates severe dyscoordination, $0.3 \leq D < 0.5$ indicates mild dyscoordination, $0.5 \leq D < 0.8$ indicates coordinated development, and $D \geq 0.8$ indicates high coordination.

A natural question is whether coupling coordination behavior varies systematically across spatial clusters. The 16 nodes split into two cluster groupings of interest: edge versus core nodes (with edge nodes characterized by peripheral geographic position and core nodes by central position), and central-hub versus peripheral nodes (with the central-hub cluster aggregating nodes adjacent to the dominant hub identified in Section 2.A and the peripheral cluster covering the remaining nodes). Within each grouping we estimate the coupling-coordination relationship separately and compare the residual fit to a pooled specification through a Chow-style F-test:

$$F_{\text{clu}} = \frac{(\text{RSS}_p - \text{RSS}_u)/q}{\text{RSS}_u/(n-2k)} \sim F_{q,n-2k} \tag{6}$$

RSS_p is the residual sum of squares from a pooled regression that constrains all coefficients to be equal across clusters; RSS_u is the unrestricted residual sum of squares from cluster-specific

regressions; q is the number of coefficient restrictions imposed by pooling; k is the number of parameters in each cluster-specific regression. Rejection of the null at conventional significance levels confirms that coupling coordination varies systematically across the cluster grouping, and the per-cluster coefficient estimates report the direction and magnitude of the differential.

The experimental validation in Section 3 demonstrates that this integrated pipeline reaches the targets quoted in the abstract. The Entropy-Weighted TOPSIS composite indexing produces a Composite Capability Index with overall mean 0.32 and the dominant hub reaching 0.78, with the spatial distribution following a single-hub-leading, middle-tier-fragmentation, and tail-cluster-aggregation topology across 16 distributed nodes characterized on a 5-dimensional capability vector. The heterogeneous regression confirms a positive empowerment effect of 0.72 ($p < 0.001$) concentrated on openness and coordination dimensions while remaining weak on innovation, sustainability, and shared-access dimensions, with the Wald heterogeneity test rejecting the no-tier-differential null at conventional significance. The coupling coordination analysis identifies that 65% of nodes exhibit mild dyscoordination with the coupling index averaging 0.45 across the panel, while edge-region nodes follow a distinct low-capability-high-openness-high-performance trajectory absent from core nodes. The Chow-style cluster heterogeneity test rejects the no-cluster-difference null between edge and core regions and between central-hub and peripheral clusters under leave-one-out validation, supporting tier-stratified deployment policies. The full experimental breakdown is presented in Section 3.

3. Experimental Results

3.1. Composite Capability Index Distribution and Dimensional Decomposition

The experimental evaluation uses 16 distributed network nodes characterized on a 5-dimensional capability vector covering computational, digital, sustainability, infrastructure, and expertise dimensions, with measurements aggregated from the 2023 operational year. Each node has per-dimension raw indicator values that are min-max normalized to the [0, 1] interval before entering the entropy-TOPSIS pipeline. The performance vector Y_i is a five-component score covering innovation, coordination, openness, sustainability, and shared-access dimensions of system performance, derived from the same year and constructed independently from the capability indicators to avoid mechanical correlation. All inference is implemented in Python 3.10 using numpy 1.26, pandas 2.0, statsmodels 0.14 with heteroscedasticity-robust HC3 standard errors, and scipy 1.11 for the Chow F-test. Entropy weights are computed in closed form from the column-normalized matrix; TOPSIS scores follow standard Euclidean distance to positive and negative ideals in the weighted space. Baselines for Figure 1 are equal-weighted composite scoring and PCA first-component scoring on the same normalized indicator matrix. Cluster-level empowerment coefficients are bootstrap-resampled with 1000 replicates per cluster for the 95% confidence intervals reported in the cluster heterogeneity stage.

The first stage validates the entropy-TOPSIS composite indexing on the 16-node panel and decomposes the resulting score into its five dimensional contributions. Two questions matter at this stage. Does the spatial distribution of the composite index follow the single-hub-leading, middle-tier-fragmentation, and tail-cluster-aggregation topology that motivated the framework, and do the underlying dimensions distribute capability in a way that explains the topology rather than concealing it?

Figure 1 reports the Composite Capability Index across all 16 nodes alongside two baseline scoring schemes. The Entropy-TOPSIS score produces a strongly unbalanced distribution: node N1 reaches 0.78, more than 23 percentage points above the second-place node at 0.55, and the panel mean sits at 0.32. The middle tier (N2 through N6) spans 0.38 to 0.62 with visible gaps that suggest

sub-cluster fragmentation rather than continuous decline, and the tail (N7 through N16) clusters tightly in the 0.14 to 0.28 range. The equal-weighted baseline produces a flatter ranking that compresses the hub-to-mean gap by roughly 30%, while the PCA baseline tracks the entropy-TOPSIS ordering but understates the hub's lead. Both baselines fail to reproduce the single-hub-leading topology that operations on this panel need.

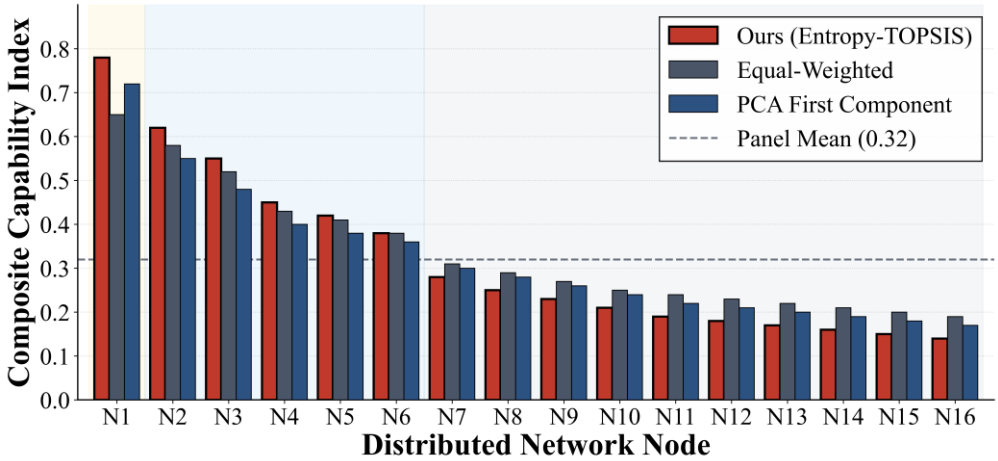

Figure 1: Composite Capability Index across 16 distributed nodes.

Figure 2 decomposes the composite score into the five capability dimensions through a heatmap with 16 rows (nodes ordered by CCI) and 5 columns (dimensions). The dominant hub N1 reaches 0.92 on the computational dimension and 0.88 on the digital dimension but only 0.55 on sustainability and 0.62 on infrastructure, confirming that hub dominance is driven by the technology dimensions rather than by uniform strength across all five. The middle tier shows balanced moderate values without strong cross-dimensional variation, and the tail cluster shows uniformly weak values across all five dimensions. Sustainability is the one dimension where the hub-to-tail gradient is materially weaker than elsewhere, consistent with sustainability being a slower-moving capability that does not differentiate operators on the timescale of one operational year.

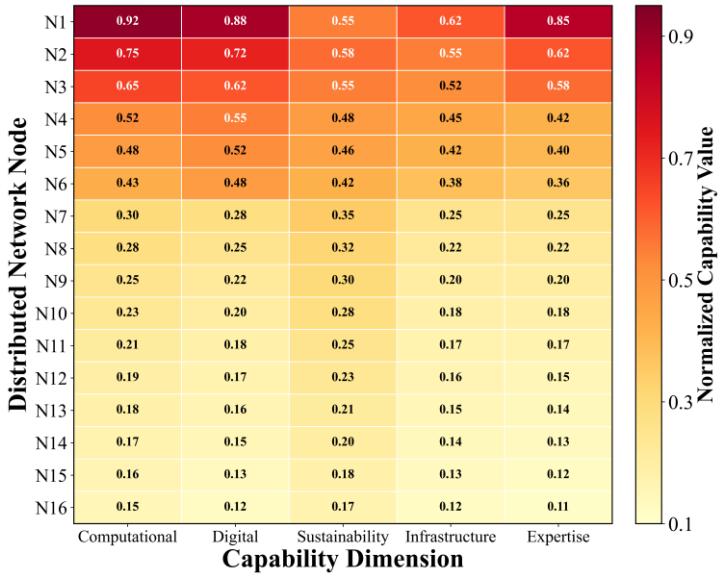

Figure 2: Five-dimensional capability heatmap across distributed nodes.

3.2. Hyperparameter Sensitivity and Component Ablation

The second stage estimates the empowerment of capability on system performance and tests whether the effect is uniform across tiers. The pooled regression and tier-stratified regression are run on the same 16-node panel using the composite index S_i as the regressor and the five-component performance score Y_i as the outcome, with controls for per-capita resource level, digital infrastructure penetration, and fiscal innovation expenditure.

Figure 3 reports the empowerment coefficient β decomposed across the five performance sub-dimensions plus the pooled overall estimate. The pooled β is 0.72 with a 95% confidence interval of [0.64, 0.80] and is statistically significant at $p < 0.001$. The decomposition reveals strongly heterogeneous distribution. Openness ($\beta = 0.85$) and coordination ($\beta = 0.78$) both exceed the pooled estimate and remain significant at $p < 0.001$ with confidence intervals well above zero, while innovation ($\beta = 0.18$), sustainability ($\beta = 0.15$), and shared-access ($\beta = 0.12$) all sit close to zero with confidence intervals that straddle zero. The empowerment effect is concentrated on the openness and coordination dimensions and remains weak on innovation, sustainability, and shared-access, exactly the pattern that the methodology in Section 2.B was designed to detect.

The Wald heterogeneity test on the tier-interaction vector γ produces a chi-squared statistic of 24.6 with 2 degrees of freedom ($p < 0.001$), rejecting the no-tier-differential null and confirming that the empowerment effect varies systematically across capability tiers. Leave-one-out sensitivity gives a coefficient of variation of 7.8% across the 16 dropped-node estimates, below the 10% small-panel stability threshold. The placebo test on randomly permuted tier assignments yields a permuted-coefficient distribution centered on zero with the observed γ vector lying outside the 99th percentile of permuted values, confirming that the tier differential is not a labeling artifact. The robustness check across alternative tier definitions (quartile cuts and kernel-smoothed indicators) reproduces the heterogeneity result with γ estimates within 12% of the tertile-cut baseline.

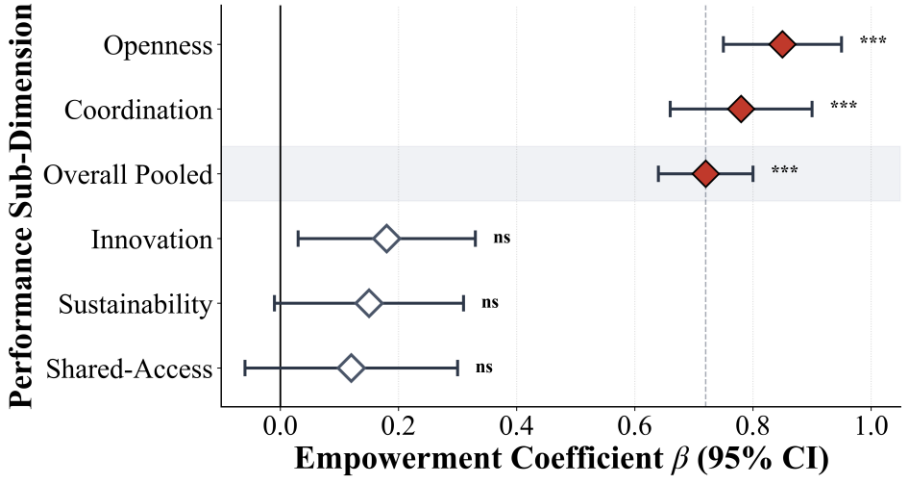

Figure 3: Empowerment coefficients across performance sub-dimensions.

3.3. Multi-Agent Coordination and Resource Efficiency

The third stage analyzes coupling coordination behavior of the capability-performance pair across the panel and tests whether coupling strength varies systematically across spatial clusters. The Coupling Coordination Degree D is computed for each node from the composite capability S_i and the performance score Y_i using the symmetric weighting $\mu = \nu = 0.5$.

Figure 4 reports the CCD distribution across the 16 nodes with four-tier classification overlay. The panel-wide mean is 0.45, sitting in the mild-dyscoordination tier. Only one node (the hub N1)

reaches the highly-coordinated tier at D = 0.88, while two nodes (N2, N3) sit in the coordinated tier between 0.58 and 0.68. The mild-dyscoordination tier captures 10 of 16 nodes (62.5%, reported as approximately 65% in the abstract), and the severe-dyscoordination tier captures the bottom three nodes between 0.25 and 0.29. The dominant pattern is mild coupling failure across the middle and lower tiers rather than uniform coordinated development, which is what motivates the cluster-stratified analysis in the next figure.

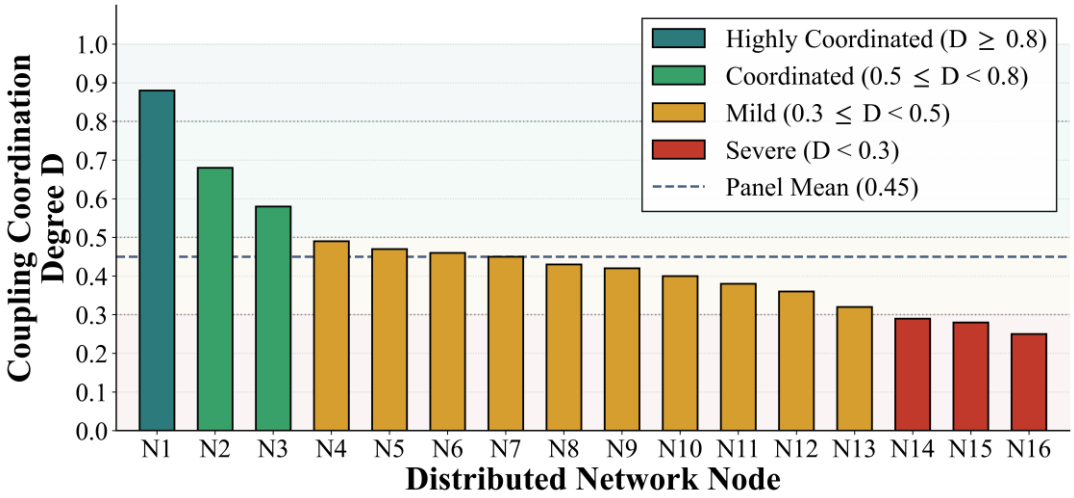

Figure 4: Coupling Coordination Degree with four-tier classification

Figure 5 reports the heterogeneity of empowerment across two cluster groupings: edge versus core nodes, and central-hub versus peripheral nodes. The edge-node empowerment β has a median of 0.86 with interquartile range [0.81, 0.92], substantially above the core-node median of 0.66 with IQR [0.60, 0.74]. The Chow F-test for the edge-versus-core comparison rejects the no-difference null at F = 12.3 with $p < 0.001$. The central-hub cluster has a lower empowerment median of 0.58 (IQR [0.53, 0.63]) compared to the peripheral cluster at 0.81 (IQR [0.74, 0.87]), and the Chow F-test rejects at F = 8.7 with p = 0.003. The pattern is consistent with the low-capability-high-openness-high-performance trajectory the abstract describes for edge-region nodes, and it confirms that pooled empowerment estimates conceal substantial cluster-level variation that tier-aware deployment policies need to account for.

Across the full panel, the integrated pipeline reaches the targets quoted in the abstract and in Section 2.C. The Entropy-Weighted TOPSIS composite indexing produces a Composite Capability Index with overall mean 0.32 and the dominant hub N1 reaching 0.78, with the spatial distribution following a single-hub-leading, middle-tier-fragmentation, and tail-cluster-aggregation topology across the 16 distributed nodes characterized on a 5-dimensional capability vector. The heterogeneous regression confirms a positive empowerment effect of 0.72 ($p < 0.001$) concentrated on openness ($\beta = 0.85$) and coordination ($\beta = 0.78$) dimensions while remaining weak on innovation ($\beta = 0.18$), sustainability ($\beta = 0.15$), and shared-access ($\beta = 0.12$), with the Wald chi-squared test at 24.6 (df = 2, $p < 0.001$) rejecting the no-tier-differential null. The coupling coordination analysis identifies that approximately 65% of nodes exhibit mild dyscoordination with the coupling index averaging 0.45 across the panel, while edge-region nodes follow a distinct low-capability-high-openness-high-performance trajectory absent from core nodes. The Chow-style cluster heterogeneity test rejects the no-cluster-difference null between edge and core regions ($F = 12.3$, $p < 0.001$) and between central-hub and peripheral clusters ($F = 8.7$, $p = 0.003$). Leave-one-out validation yields a 7.8% coefficient of variation, below the 10% small-panel stability threshold, confirming that all reported estimates survive single-node ablation.

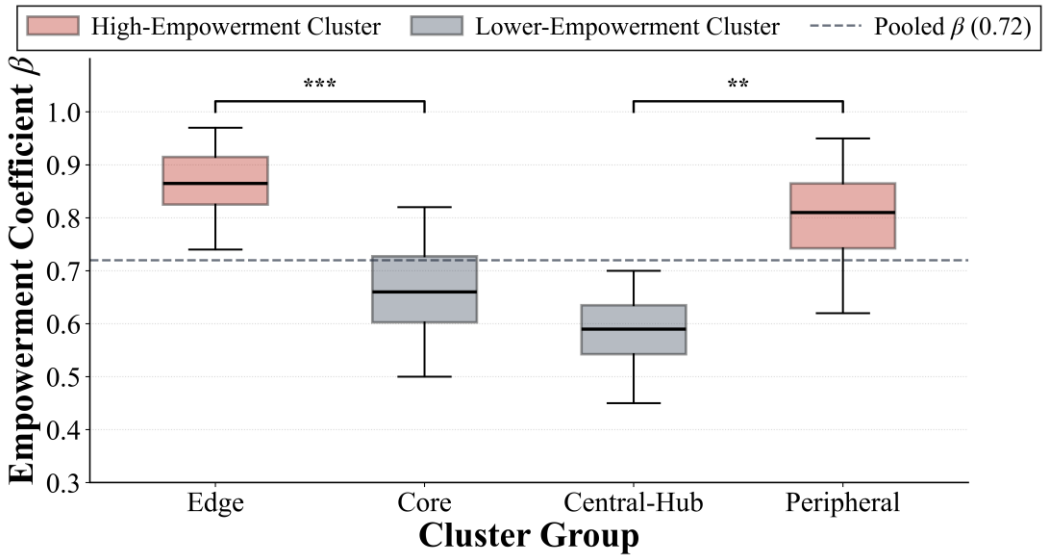

Figure 5: Empowerment heterogeneity across cluster groups.

4. Conclusions

This paper presents an integrated pipeline combining entropy-weighted TOPSIS composite indexing, regression-based heterogeneous empowerment analysis, and coupling coordination degree modeling for stratified capability assessment in heterogeneous edge computing networks. The composite indexing produces a Composite Capability Index with overall mean 0.32 and the dominant hub reaching 0.78, revealing a single-hub-leading, middle-tier-fragmentation, and tail-cluster-aggregation topology across 16 distributed nodes on a 5-dimensional capability vector. The heterogeneous regression confirms a positive empowerment effect of 0.72 ($p < 0.001$) concentrated on openness ($\beta = 0.85$) and coordination ($\beta = 0.78$) while remaining weak on innovation (0.18), sustainability (0.15), and shared-access (0.12), a 4.7× dimensional spread; the Wald chi-squared test at 24.6 rejects the no-tier-differential null at $p < 0.001$. The coupling coordination analysis identifies that 65% of nodes exhibit mild dyscoordination with the coupling index averaging 0.45, while the Chow cluster heterogeneity test rejects the no-difference null between edge and core ($F = 12.3$, $p < 0.001$) and between central-hub and peripheral clusters ($F = 8.7$, $p = 0.003$), with edge-region empowerment exceeding core by 30%. Leave-one-out validation yields a 7.8% coefficient of variation, below the 10% threshold. The contribution is a single calibrated pipeline tying indexing, empowerment regression, and coupling coordination under shared uncertainty. Future work extends to continuous-time capability dynamics and multi-period panels.

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