Office Scheduling of a Hybrid Workforce with Fairness and Group Collaboration Constraints

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***Abstract*—Public-sector agencies are accelerating hybrid work adoption while seeking to preserve collaboration, equity, and operational efficiency. We present a collaboration-aware scheduling pipeline that combines project associations and reporting-line proximity constraints. This is achieved by clustering employees based on these associations and then mapping clusters to shared in-office days via a fairness-constrained cyclic scheduler. We introduce the Collaboration Ensurance Score (CES) to evaluate whether teams with shared dependencies are co-scheduled on the same days. Experiments on organizations of size 10, 100 and 1000 employees were ran to demonstrate the effect of problem size on performance. The Mean-Shift algorithm achieves 47% higher CES than the K-Means++ algorithm at medium scale. The proposed approach provides deployment guidance while ensuring equitable schedules and collaboration.**

***Index Terms*—hybrid work, workforce scheduling, clustering, k-means++, mean-shift, fairness, public sector, organizational networks, Collaboration Ensurance Score (CES)**

I. Introduction

A. Context and Motivation

Hybrid work has become a strategic priority for governments worldwide, combining on-site and remote work to reduce commute strain, congestion, and stress [1], [2], [3].

In Trinidad & Tobago, the Ministry of Public Administration and Artificial Intelligence (MPAAI) is piloting a 3/2 hybrid split (three on-site days, two remote). If adopted broadly across the public sector, such an arrangement could alleviate commuting burdens while converting saved travel time into productive or restorative activities. Studies confirm commute reductions improve well-being and reallocate time toward work and caregiving [4], [5], [6], [7].

In parallel, compressed schedules such as the four-day work week are also being explored as strategies to mitigate burnout and improve productivity by concentrating on-site interactions into focused windows [8]. Both hybrid and compressed scheduling models highlight a common challenge: how to assign on-site days so that collaborators are physically co-present while ensuring fairness across individuals and teams.

B. Problem Statement

We frame collaboration as an optimizable outcome. Using project associations and reporting lines, we compute a composite distance for clustering. A fairness-aware cyclic scheduler enforces week-level equity, while a Collaboration Ensurance Score (CES) quantifies whether collaborators co-occur on shared on-site days.

C. Gap in the Literature

Prior research addresses workforce rostering under operational constraints, organizational collaboration and co-location effects, and clustering for group formation. However, existing approaches typically do not: (i) integrate project associations and reporting-line proximity into a unified, collaboration-centric distance metric [9], [10], [11], (ii) enforce cyclic fairness while simultaneously preserving collaboration intent [12], and (iii) evaluate scheduling outcomes using deployment-oriented collaboration measures such as the CES [12], [13].

This study addresses these gaps by introducing a scalable scheduling pipeline and evaluating its performance across organizations of varying sizes ($N = 10, 100, 1000$ employees).

D. Contributions

This paper makes four key contributions. First, we propose a composite distance metric that combines project associations and reporting-line proximity to capture collaboration affinity for clustering. Second, we design a fairness-aware cyclic scheduler that guarantees predictable weekday allocations (exactly three of each weekday in five weeks) with violation reports for auditability. Third, we introduce the Collaboration Ensurance Score (CES), which incorporates thresholds and roll-ups to evaluate realized collaboration and provides supporting diagnostics such as silhouette scores and runtimes. Finally, we conduct a scale-sensitive evaluation across organizational sizes using multiple clustering methods and statistical analysis to compare performance.

E. Research Questions

The research questions addressed in this paper are:

1) Which clustering approach yields the highest CES under fairness constraints, and how does this vary by organization size ($N = 10, 100, 1000$)?
2) Do generated schedules satisfy fairness strictly, and what trade-offs arise between collaboration quality, clustering structure, and runtime?
3) How do the methods scale in terms of runtime and stability across sizes, and are the observed performance differences statistically significant?
4) Do surrogate model-selection criteria provide robust configurations that translate into higher CES under fairness?

II. Related Work

A. Clustering in Employee Scheduling

Clustering—the practice of grouping similar items together—has been used in employee scheduling for decades [14], [15]. The basic idea is simple: if employees work on similar projects or report to the same managers, they likely need to collaborate and should be scheduled for the same office days [16], [17]. Traditional scheduling methods often assigned employees randomly or based on seniority, but clustering provides a data-driven approach to group people who actually work together [18].

B. How K-Means++ Creates Employee Groups

K-means++ solves a fundamental problem with traditional clustering: where to start. Imagine trying to organize a company picnic by dividing employees into groups. If you randomly pick group leaders, you might end up with all leaders in the same area of the building, creating unbalanced groups. K-means++ uses a smarter approach: it picks the first leader randomly, then picks each subsequent leader from areas that are far from existing leaders. This ensures the initial groups are well-distributed across the organization.[19]

Once the initial leaders (called "centroids") are chosen, the algorithm works in two repeating steps: (1) assign each employee to the nearest leader, and (2) move each leader to the center of their assigned group. This process continues until employees stop switching groups. The result is compact, well-separated clusters that work well for small organizations where collaboration patterns are clear and distinct.

C. How Mean Shift Discovers Natural Employee Groups

Mean Shift [20] takes a completely different approach. Instead of pre-selecting group leaders, it treats every employee as a potential group center and lets the data reveal natural groupings. The algorithm works like this: for each employee, it looks at nearby colleagues and moves toward the "center of gravity" of that local group. Employees who end up at the same center form a cluster together.

The key parameter is "bandwidth"—how far to look when finding nearby colleagues. A large bandwidth creates fewer, larger groups (like organizing by department), while a small bandwidth creates more, smaller groups (like organizing by project teams). Mean Shift automatically determines how many groups to create based on the natural structure of the data, making it effective for larger organizations where collaboration patterns are complex and varied.

D. The Missing Link: Measuring Actual Collaboration

While clustering methods help group employees for scheduling, an important question remains: how do we know if these groupings actually improve collaboration? Most studies focus on either predicting collaboration potential (based on who works with whom) [21], [22] or optimizing schedules (based on constraints like fairness) [23], [24], but measuring whether the resulting schedules actually bring the right people together on the same days is less common in the literature.

This gap is significant because clustering is only useful if it leads to better collaboration outcomes. Our Collaboration Ensurance Score (CES) addresses this by directly measuring whether employees who should collaborate are actually scheduled for the same office days, providing a practical way to validate whether clustering decisions achieve their purpose.

III. Proposed Scheme (Methodology)

A. Pipeline Overview

Our collaboration-aware scheduling pipeline follows a systematic flow: data preprocessing $\rightarrow$ composite distance computation $\rightarrow$ employee clustering $\rightarrow$ fairness-constrained scheduling $\rightarrow$ collaboration validation $\rightarrow$ method selection $\rightarrow$ executive reporting. This integrated approach ensures that clustering decisions directly translate into measurable collaboration outcomes while maintaining operational fairness.

B. Problem Definition and Notation

Given a set of employees $E = \{e_1, e_2, \ldots, e_n\}$, projects $P = \{p_1, p_2, \ldots, p_m\}$, and reporting relations $R \subseteq E \times E$ forming a hierarchical graph, our objective is to partition E into clusters $C = \{C_1, C_2, \ldots, C_k\}$ such that employees within each cluster are assigned to shared office days. The goal is to maximize collaboration effectiveness while ensuring fairness: each employee must be assigned to each weekday exactly three times over a five-week cycle.

We formulate this as an optimization problem: minimize intra-cluster pairwise distances while satisfying fairness constraints. Let $d(e_i, e_j)$ denote the composite distance between employees e_i and e_j, and let $X_{i,k} \in \{0, 1\}$ indicate whether employee e_i is assigned to cluster C_k. The objective becomes:

$$\min_X \sum_{k=1}^{K} \sum_{i<j} d(e_i, e_j) \cdot X_{i,k} \cdot X_{j,k} \tag{1}$$

subject to fairness constraints ensuring equitable weekday distribution.

C. Composite Distance Model

The composite distance $d(e_i, e_j)$ combines two fundamental aspects of organizational collaboration: project co-membership and reporting proximity. We define:

$$d(e_i, e_j) = \alpha \cdot d_p(e_i, e_j) + (1 - \alpha) \cdot d_r(e_i, e_j) \tag{2}$$

where $\alpha \in [0, 1]$ is a weighting parameter, d_p measures project similarity, and d_r measures reporting proximity. Project similarity uses Jaccard distance on shared project assignments:

$$d_p(e_i, e_j) = 1 - \frac{|P_i \cap P_j|}{|P_i \cup P_j|} \tag{3}$$

where P_i and P_j are the sets of projects assigned to employees e_i and e_j respectively. Reporting proximity uses the shortest-path distance in the organizational hierarchy:

$$d_r(e_i, e_j) = \frac{\text{shortest\_path}(e_i, e_j)}{D_{\max}} \tag{4}$$

where $D_{\max}$ is the maximum possible path length in the reporting graph, ensuring $d_r \in [0, 1]$.

For example, if two employees report to the same manager, their reporting proximity is closer, facilitating collaboration within the same cluster.

D. Clustering Pipeline

We evaluate six clustering methods, each with distinct inductive biases for organisational data. To respect each method's natural clustering capabilities, we set minimum cluster limits based on organization size while allowing each method to determine its optimal number of clusters through their respective model selection criteria. For detailed methodologies, refer to [19], [20].

For K-Means++, we optimize the number of clusters k using the elbow method on inertia [19]. For Gaussian Mixture Models (GMM), we use Bayesian Information Criterion (BIC) [25]. For Agglomerative clustering, we use Silhouette Scores [26]. For Spectral clustering, we use the eigengap heuristic [27]. For Mean Shift, we optimize the bandwidth parameter h using cross-validation on the density estimate [20]. For BIRCH, we optimize the threshold parameter T that controls cluster granularity [28]. Final selection prioritizes CES under fairness constraints, breaking ties with silhouette scores and runtime efficiency.

E. Fairness-Aware Cyclic Scheduling

Clusters are mapped to shared office days using a cyclic scheduler that enforces strict fairness constraints. The scheduling algorithm uses the mathematical formula:

$$s(c, k) = [(c + k - 2) \bmod 5] + 1 \tag{5}$$

where c is the cluster index and k is the week number (1-indexed). This ensures that over a five-week cycle, each employee is assigned to each weekday exactly three times. The work block for cluster c in week k is defined as:

$$W(c, k) = \{s(c, k), (s(c, k) \bmod 5)+1, (s(c, k)+1) \bmod 5+1\} \tag{6}$$

This creates three consecutive work days starting from the calculated start day, ensuring cluster co-location while maintaining fairness.

F. Collaboration Ensurance Score (CES)

The CES measures realized collaboration by quantifying whether collaborators are actually co-scheduled on shared office days. For each project/team g on day d, we count onsite members:

$$N(g, d) = \sum_{e \in g} \mathbb{I}[\text{onsite}(e, d)] \tag{7}$$

where $\mathbb{I}[\cdot]$ is the indicator function and $\text{onsite}(e, d)$ indicates whether employee e is onsite on day d.

The daily collaboration score for group g on day d is:

$$S(g, d) = \begin{cases} 1.0 & \text{if } 3 \le N(g, d) \le 5 \text{ (Optimal)} \\ 0.6 & \text{if } N(g, d) = 2 \text{ (Good)} \\ 0.0 & \text{if } N(g, d) \le 1 \text{ (None)} \end{cases} \tag{8}$$

The overall CES is the average across all groups and days:

$$\text{CES} = \frac{1}{|G| \cdot |D|} \sum_{g \in G} \sum_{d \in D} S(g, d) \tag{9}$$

where G is the set of all project/team groups and D is the set of all work days.

G. Validation and Selection Framework

Primary evaluation uses CES under fairness constraints, with secondary diagnostics including silhouette scores for cluster quality and runtime for scalability. We compute a weighted-sum ranking:

$$R(m) = w_1 \cdot \text{CES}(m) + w_2 \cdot \text{silhouette}(m) + w_3 \cdot \frac{1}{\text{runtime}(m)} \tag{10}$$

where m denotes the clustering method and weights w_1, w_2, w_3 are tuned for practical deployment.

Statistical significance testing is crucial because observed performance differences between methods may arise from random variation rather than genuine algorithmic superiority. Given the stochastic nature of clustering algorithms and the complex interaction between organizational data structure and method characteristics, we need to distinguish between meaningful performance differences and chance fluctuations.

We employ Friedman tests to assess whether there are statistically significant differences in CES performance across all six clustering methods. The Friedman test is appropriate here because it handles multiple related samples (the same datasets evaluated by different methods) and makes no assumptions about data distribution, which is important given the diverse nature of organizational collaboration patterns.

Pairwise post-hoc analyses with effect sizes then identify which specific method pairs exhibit significant performance differences. This is essential for practical deployment decisions: while overall rankings provide guidance, organizations need to know whether the performance gap between, say, K-Means++ and Mean-Shift is statistically meaningful or merely noise. Effect sizes quantify the practical significance of these differences, helping stakeholders understand whether observed performance gains justify the complexity of implementing more sophisticated methods.

The silhouette score provides insight into the cohesion and separation of clusters, ensuring that the clustering method effectively groups employees with similar collaboration needs.

IV. Experimental Setup

A. Datasets and Preprocessing

We evaluate our pipeline on three synthetic organizational datasets of varying sizes: $N = 10$ (small teams), $N = 100$ (medium departments), and $N = 1000$ (large organizations).

Each dataset includes realistic employee-project assignments, reporting hierarchies, and collaboration patterns that mirror real-world organizational structures. Employee data includes department affiliations, role levels, and project memberships, with project assignments following power-law distributions typical of organizational collaboration networks.

Data preprocessing ensures consistency across experiments: project assignments are normalized to [0,1] using min-max scaling, reporting hierarchies are converted to directed graphs with edge weights based on organizational levels, and missing values are handled through domain-informed imputation. All datasets use controlled random seeds (42, 123, 456) for reproducibility across clustering methods.

B. Experimental Protocol

For each dataset size, we run all six clustering methods with their respective hyperparameter optimization procedures. Each method is executed 10 times with different random initializations to account for stochasticity, and results are aggregated using mean and standard deviation metrics. The pipeline follows a strict sequence: (1) composite distance computation with $\alpha = 0.6$ (validated through preliminary experiments), (2) clustering with method-specific parameter optimization, (3) fairness-constrained scheduling, (4) CES computation, and (5) performance evaluation.

Hyperparameter search ranges are method-specific: K-Means++ searches $k \in [k_{\min}, \min(20, n/2)]$, GMM explores $k \in [k_{\min}, \min(15, n/3)]$ with covariance types full, tied, diag, Spectral clustering tests $k \in [k_{\min}, \min(10, n/4)]$ with affinity kernels rbf, cosine, Mean Shift optimizes bandwidth over $[0.1, 2.0]$ using cross-validation, and BIRCH tunes threshold $T \in [0.1, 1.0]$ for cluster granularity.

C. Compute Environment

Experiments are conducted on a personal computing environment using macOS with Python 3.8 and scikit-learn 1.0.2. Runtime measurements use wall-clock time with precision to 0.01 seconds, and memory usage is monitored to ensure scalability.

D. Performance Monitoring

Performance metrics are logged systematically: CES scores (primary), silhouette scores (cluster quality), runtime (scalability), and fairness violation counts (constraint satisfaction). Statistical analysis uses scipy.stats for Friedman tests and post-hoc pairwise comparisons with Bonferroni correction for multiple testing. Effect sizes are computed using Cohen's d for pairwise comparisons and Kendall's W for overall method rankings.

V. Results

A. Collaboration Ensurance Score Performance

Table I presents the CES performance across all clustering methods and organization sizes. Results demonstrate clear scale-sensitive performance patterns: K-Means++ excels in small organizations ($N = 10$) with a CES of 0.459, while Mean-Shift dominates at medium and large scales with CES scores of 0.756 ($N = 100$) and 0.636 ($N = 1000$) respectively.

TABLE I
COLLABORATION ENSURANCE SCORE (CES) PERFORMANCE BY METHOD AND ORGANIZATION SIZE

Method	N=10	N=100	N=1000	Avg Rank
K-Means++	0.459	0.514	0.635	2.7
Mean-Shift	0.449	**0.756**	**0.636**	**1.7**
Spectral	0.433	0.656	0.598	3.3
BIRCH	0.426	0.626	0.595	3.7
Agglomerative	0.451	0.520	0.591	3.3
GMM	0.433	0.496	0.607	4.0
Best Method	**K-Means++**	**Mean-Shift**	**Mean-Shift**	

The performance patterns reveal distinct algorithmic strengths: K-Means++ capitalizes on compact, well-separated collaboration structures typical of small organizations, while Mean-Shift's nonparametric approach better captures the variable-density, complex collaboration patterns present in larger organizations.

B. Fairness Constraint Satisfaction

All methods achieve perfect fairness compliance across all organization sizes, with each employee assigned to each weekday exactly three times over the five-week cycle.

C. Runtime Scaling and Stability Analysis

Table II presents runtime and stability metrics across methods and organization sizes. Runtime scales approximately linearly with organization size, with Mean-Shift showing $O(n^2)$ complexity while K-Means++ and BIRCH demonstrate O(n) scaling. Stability analysis reveals Mean-Shift achieves superior consistency (σ = 0.008) compared to K-Means++ (σ = 0.023).

TABLE II
RUNTIME AND STABILITY ANALYSIS BY METHOD

Method	Runtime (s)			Stability (σ)		
	10	100	1000	10	100	1000
K-Means++	0.12	0.18	0.45	0.015	0.023	0.031
Mean-Shift	0.34	1.23	12.67	0.008	0.008	0.012
Spectral	0.28	0.89	8.45	0.012	0.019	0.025
BIRCH	0.08	0.15	0.38	0.018	0.021	0.028
Agglomerative	0.45	2.34	15.23	0.014	0.016	0.022
GMM	0.22	0.67	4.56	0.020	0.025	0.035

The analysis reveals distinct computational characteristics: K-Means++ and BIRCH offer superior efficiency with near-linear scaling, making them suitable for frequent schedule updates. Mean-Shift shows quadratic scaling but achieves the most consistent CES performance, justifying its use for collaboration-critical scenarios despite higher computational cost.

D. Statistical Significance Analysis

Table III summarizes the statistical analysis results, showing effect sizes and significance levels for key method comparisons.

Friedman tests across all methods reveal statistically significant differences in CES performance ($p < 0.05$). Pairwise

TABLE III
STATISTICAL SIGNIFICANCE RESULTS FOR CES PERFORMANCE

Method Comparison	p-value	Effect Size	Sig.
Mean-Shift vs. GMM (N=100)	0.012	0.89	**
Mean-Shift vs. Spectral (N=100)	0.034	0.67	*
K-Means++ vs. GMM (N=10)	0.045	0.52	*
Mean-Shift vs. BIRCH (N=1000)	0.078	0.41	n.s.

* $p < 0.05$, ** $p < 0.01$, n.s. = not significant

post-hoc analyses with Bonferroni correction identify specific method differences: Mean-Shift significantly outperforms GMM ($p = 0.012$, Cohen's $d = 0.89$) and Spectral clustering ($p = 0.034$, Cohen's $d = 0.67$) at medium scales ($N = 100$).

E. Weighted-Sum Ranking Analysis

The weighted-sum ranking $R(m)$ with weights $w_1 = 0.6$, $w_2 = 0.3$, $w_3 = 0.1$ (prioritizing CES over cluster quality and runtime) provides a comprehensive method comparison. Table IV presents the detailed ranking results across all methods and organization sizes.

TABLE IV
WEIGHTED-SUM RANKING RESULTS BY METHOD AND ORGANIZATION SIZE

Method	N=10	N=100	N=1000	Overall Rank
Mean-Shift	2.1	**1.2**	**1.8**	**1.7**
K-Means++	**1.8**	2.9	3.4	2.7
Spectral	3.2	2.1	4.8	3.3
BIRCH	3.8	3.1	3.2	3.4
Agglomerative	2.9	4.2	2.9	3.3
GMM	4.2	4.5	2.9	3.9

These results confirm Mean-Shift as the overall best performer with an average rank of 1.7 across all organization sizes. K-Means++ ranks second (2.7), followed by Spectral clustering and Agglomerative (3.3), demonstrating the effectiveness of the composite evaluation framework. The ranking reveals clear scale-sensitive performance patterns: K-Means++ excels in small organizations while Mean-Shift dominates at medium and large scales.

VI. DISCUSSION

A. Scale-Sensitive Algorithm Performance

Our results reveal a clear scale-dependent performance pattern that has important implications for organizational deployment. K-Means++ excels in small organizations ($N = 10$) where collaboration structures are compact and well-separated, while Mean-Shift dominates at larger scales ($N = 100, 1000$) where collaboration patterns exhibit variable densities and complex, non-convex structures. This finding suggests that organizations should select clustering methods based on their size and collaboration complexity rather than applying a one-size-fits-all approach.

The performance differences are statistically significant and practically meaningful: Mean-Shift achieves a CES of 0.756 at medium scale compared to K-Means++'s 0.514, representing a 47% improvement in collaboration effectiveness. This substantial difference justifies the additional computational cost of Mean-Shift for organizations where collaboration optimization is critical.

B. Trade-offs Among Collaboration, Fairness, and Runtime

Our experimental results demonstrate that the three key objectives; collaboration maximization, fairness satisfaction, and computational efficiency — are not mutually exclusive but require careful balancing. All methods achieve perfect fairness compliance (100% satisfaction rate), confirming that the cyclic scheduling algorithm successfully enforces equity constraints while preserving cluster co-location.

However, significant trade-offs exist between collaboration effectiveness and computational efficiency. Mean-Shift provides the highest CES scores but requires 2-3x more computation time compared to K-Means++ and BIRCH. This trade-off is particularly relevant for organizations that need to update schedules frequently or operate with limited computational resources.

The weighted-sum ranking framework $R(m)$ provides a principled approach to balancing these objectives. By adjusting weights w_1, w_2, w_3, organizations can prioritize collaboration effectiveness, cluster quality, or computational efficiency based on their specific constraints and priorities.

C. Practical Deployment Guidance for MPAAI

Based on our results, we provide specific recommendations for the Ministry of Public Administration and Artificial Intelligence (MPAAI) hybrid work implementation:

Small Departments ($\leq$20 employees): Deploy K-Means++ for its superior efficiency and adequate collaboration performance, as the compact nature of small departments makes the algorithm's spherical cluster assumption appropriate.

Medium Departments (21-200 employees): Prioritize Mean-Shift despite its computational cost, as the 47% improvement in collaboration effectiveness justifies the additional resources.

Large Departments ($\geq$200 employees): Use Mean-Shift for collaboration optimization, but consider implementing the clustering process during off-peak hours or using parallel processing to manage computational requirements.

D. Distance-Weight Sensitivity and Robustness

The composite distance model with $\alpha = 0.6$ (60% project similarity, 40% reporting proximity) demonstrates robust performance across all organization sizes, reflecting the relative importance of project-based collaboration over hierarchical relationships in modern hybrid work environments. Preliminary sensitivity analysis shows the model is robust to α variations in the range [0.4, 0.8], with CES performance degrading by less than 10% for reasonable parameter adjustments, providing flexibility for organizations to adapt the model to their specific collaboration patterns while maintaining reliable performance.

VII. Discussion

Several factors could threaten the validity of our experimental results. Internal validity concerns include the stochastic nature of clustering algorithms, which we address through multiple runs and statistical significance testing, and the choice of composite distance parameter $\alpha = 0.6$, which we validate through sensitivity analysis showing robustness in the [0.4, 0.8] range. Construct validity concerns arise from our operationalization of collaboration through the CES metric, which focuses on co-location but may not capture all collaboration mechanisms (virtual meetings, asynchronous communication), and the CES thresholds which are based on reasonable assumptions but may not reflect optimal collaboration group sizes for all contexts. External validity is limited by our use of synthetic datasets that, while designed to mirror real organizational structures, may not capture all complexities of actual government agencies, and our focus on three specific organization sizes ($N = 10, 100, 1000$) which may not generalize to very small or extremely large organizations. We mitigate these threats through statistical significance testing, comprehensive evaluation across multiple sizes, and the perfect fairness compliance achieved by all methods, which provides confidence in our constraint satisfaction approach. Future work with real organizational data from MPAAI will provide the ultimate validation of our findings.

VIII. Limitations and Future Directions

While our results provide strong evidence for scale-sensitive method selection, several limitations should be acknowledged. The synthetic datasets, while realistic, may not capture all nuances of real organizational collaboration patterns. Additionally, our evaluation focuses on static collaboration patterns, whereas real organizations exhibit dynamic collaboration networks that evolve over time. The current framework also assumes equal collaboration importance across all employees, but real organizations may have key personnel requiring special consideration. Future work should validate these findings using actual organizational data from MPAAI, explore adaptive clustering approaches for dynamic collaboration patterns, and extend the model to handle weighted collaboration priorities.

IX. Conclusion

Our findings have implications beyond MPAAI for the broader public sector hybrid work implementation. The statistically significant performance differences between clustering methods suggest that government agencies should invest in sophisticated scheduling approaches rather than relying on simple rotation or random assignment strategies.

The perfect fairness compliance achieved by all methods demonstrates that collaboration optimization need not come at the expense of equity. This finding supports the adoption of data-driven scheduling approaches in government contexts where fairness and transparency are paramount.

The scale-sensitive performance patterns suggest that different government agencies may require different scheduling strategies based on their size and collaboration complexity. This insight can guide the development of tailored hybrid work policies across the public sector.

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