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A COMPARATIVE STATISTICAL ANALYSIS OF STAFFING DYNAMICS AND RECRUITMENT VOLATILITY IN MAYURBHANJ AND BALASORE DISTRICTS

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Abstract
This research presents a longitudinal comparative and statistical analysis of staffing dynamics within the Mayurbhanj and Balasore districts of Odisha from 2016 to 2024. The study evaluates the equilibrium between academic (teaching) and administrative (non-teaching) personnel relative to sanctioned post capacities. Utilizing an eight-year dataset, the research methodology incorporates descriptive statistics (Mean, Standard Deviation, CV%), inferential testing (Independent Samples T-Tests, Pearson Correlation), and a custom Weighted Efficiency Index.The findings reveal a significant recruitment pivot in 2023–2024, where Mayurbhanj's teaching workforce nearly tripled from its 2021 low (33 to 93), resulting in high volatility (CV: 42.2%). Conversely, a chronic support staff crisis was identified; Balasore experienced a steady workforce depletion reaching a record 68.9% vacancy rate, while Mayurbhanj remained perfectly stagnant with zero net change in eight years (SD = 0.00). Statistical testing confirms that the districts operate under divergent management priorities: Balasore maintains a significantly higher teaching volume (p = 0.001), whereas Mayurbhanj possesses a statistically superior, albeit frozen, support structure (p < 0.0001).The Weighted Efficiency Index concludes that Mayurbhanj (53.6) currently leads Balasore (50.4) in operational health due to its administrative stability. The results indicate a critical decoupling of hiring cycles, where classroom expansion is outpacing the administrative backbone. The study recommends an urgent transition from "mass hiring spikes" to phased recruitment models and the immediate filling of non-teaching vacancies to prevent a total collapse of district-level educational infrastructure.

Keywords: Staffing Dynamics, Comparative Statistical Analysis, Mayurbhanj District, Balasore District, Educational Personnel.

Introduction
Human capital development (HCD) is central to mission of higher education. In higher education, faculty members are the primary agents who create, curate, and transmit knowledge; their adequacy—in number, qualifications, and competencies—directly shapes student learning, research productivity, institutional reputation, and local innovation systems. This chapter examines the problem of insufficient faculty members in higher education institutions across Mayurbhanj and Balasore districts in Odisha. It frames the shortage not merely as a staffing gap but as a systemic human-capital challenge involving recruitment, working conditions, governance, and local socioeconomic dynamics.

The chapter is written as how faculty insufficiency shapes human capital development in higher education institutions in two districts Mayurbhanj and Balasore. It integrates theory, context and field evidence to A) Faculty insufficiency B) document its prevalence and manifestations C) analyse its effect on teaching learning, research etc D) propose feasible policy and institutional response.

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Review of literature

Human capital is a strategic factor in production (Son, 2010) as it represents the cognitive competencies, skills, relational behavior and knowledge of individuals that enhance productive output (Shuller, 2000) that eventually contributes to organization productive performance (Shuller, 2000; Son, 2010). Resources based view (RBV) articulation on the internal firm resources as a form of competitive advantage (Hoskisson, Hitt, Wan & Yiu, 1999) gave value to the strategic importance of people in an organization. RBV brought to light the added value of people in organization strategic management literature by defining and linking concepts such as knowledge (Argote & Ingram, 2000; Grant, 1996), dynamic capability (Eisenhardt & Martin, 2000; Teece, Pisano &Schuen, 1997; Barreto, 2010), organization learning (Fiol & Lyles, 1985; Fisher & White, 2000), and organizational leadership (Norburn& Birley, 1988) to strategic organizational performance. Changes in both external and internal environments may affect organizational performance (Chattopadhyay, Glick, & Huber, 2001) therefore; HCDA's are used to enhance knowledge and use it to strategically attain firm value (Petty & Guthrie, 2000). The ability to increase intellectual knowledge in the organization creates increased productivity (Petty & Guthrie, 2000). HCDA such as training has been linked to skill building and knowledge building which results to organization productivity (Goldstein & Gilliam, 1990). Research done by Black and Lynch (2001) on the manufacturing and non-manufacturing sectors on the link between knowledge improvement training and productivity revealed that for manufacturing the greater the proportion of time spent in formal employee training the higher the organizational productivity. For non-manufactures the content of training programs provided by employers seems to have an important impact on firm productivity. Organizations have shifted their outlooks about HCDA from a stand-alone event to an entirely integrated, strategic component of the firm (Salas & Cannon-Bowers, 2001). Strategically, even though a firm may have a great strategic plan in place, if the human capital is not developed to a point where they have access to the relevant knowledge, skills, and attitudes to successfully support or carry out the strategic plan, the plan is watered down (Sum, 2010) With the cost of human capital development today running into billions of dollars annually (Green, Patel, Lemke &Bussenger, 2010), investments made in human capital development approaches require justification in terms of improved organizational performance (Huselid, 1995; Shuller, 2000). As a result different human capital development approaches, including action learning (Freedman, 2011; Kuhn &Marsick, 2005),just-in time training(Beckett, Agashae& Oliver 2002) , mentoring (Allen et al., 2004; Kram,1985), coaching (Wales, 2002; Locke, 2008) and technology simulation (Read & Kleiner, 1996)have been a key in influencing the sphere of knowledge development. Firms operating in knowledge based environment are said to be more dependent on employee knowledge (Porter, 2000). Therefore, the approach used to develop human capital has a significant contributing linking factor to the outcome of knowledge retention therefore; the performance of the firm(Sum, 2010).

Many scholars have embarked on looking at the knowledge based view of the firm (Demsetz, 1988; Conner & Prahalad, 1996; Kogut & Zander, 1992; Grant, 1996; Madhok, 1996) in the hope of developing it into a theoretical status. Knowledge is among the valuable resource to the firm that is protected and ways are sorted by the management on how to organize it and efficiently generate knowledge and capability (Nickerson & Zenger, 2004). How and what knowledge is imparted and integrated into the firm influences the competitive edge that results from use (Eisenhardt & Martin, 2000; Grant, 1996). Knowledge based view as a strategic Formulator is reinforced by its main components: the people who are the knowledge carriers and the agents of the business (Sveiby, 2001); organizational structures created by the people toallow interaction as well as self-expression (Weick, 1983; Sveiby, 2001); transfer capabilities of knowledge both internal and external (Sveiby, 2001); and knowledge management (Nickerson &Zenger, 2004; Bencsik & Sólyom, 2011). The literature advances the idea that human capital development approaches is a basic entity of knowledge generation (Sum, 2010) which results to strategically using the acquired knowledge and hence evoking firm performance (Conner & Prahalad, 1996; Eisenhardt & Martin, 2000). This connected depiction triggers the model described in this paper based on Grants (1996) characteristics that are pertinent to utilization of knowledge within the firm to create value.

Scarborough and Elias (2002) believe that: ‘the concept of human capital is most usefully viewed as a bridging concept – that is, it defines the link between HR practices and business performance in terms of assets rather than business processes.’ They point out that human capital is to a large extent ‘non-standardized, tacit, dynamic, context dependent and embodied in people’. These characteristics make it difficult to evaluate human capital bearing in mind that the ‘features of human capital that are so crucial to firm performance are the flexibility and creativity of individuals, their ability to develop skills over time and to respond in a motivated way to different contexts’. It is indeed the knowledge, skills and abilities of individuals that create value, which is why the focus has to be on means of attracting, retaining, developing and maintaining the human capital they represent. Davenport (1999) comments that: People possess innate abilities, behaviours and personal energy and these elements make up the human capital they bring to their work. And it is they, not their employers, who own this capital and decide when, how and where they will contribute it. In other words, they can make choices. Work is a two-way exchange of value, not a one-way exploitation of an asset by its owner. The choices they make include how much discretionary behaviour they are prepared to exe

Objectives

1. To measure the extent and patterns of faculty insufficiency across higher educational Institutions in Mayurbhanj and Balasore Districts.
2. To assess the effects of faculty insufficiency on teaching-learning processes, research output, student outcomes and equity.

Hypothesis

1. **Null Hypothesis (H0)**: There is no significant difference in staffing levels between the two districts.
2. **Alternative Hypothesis (H1)**: There is significant difference in staffing levels between the two districts.

Methodology

The methodology for this comparative analysis followed a structured four-stage statistical process to evaluate staffing dynamics across Mayurbhanj and Balasore by using both primary and secondary data with a semi structured questionnaire.

Data Preparation and Normalization

1. **Variable Definition**: Secondary data was categorized into four primary quantitative variables: Sanctioned Posts, Men in Position (MIP), and Vacancies for both Teaching and Non-Teaching staff.
2. **Time-Series Baseline**: 2016-2017 was established as the T0 baseline to measure cumulative growth or loss of personnel over the 8-year study period.

Descriptive Statistical Analysis

1. **Central Tendency**: Calculated the **Arithmetic Mean** of personnel (MIP) to establish the average operational capacity for each district.
2. **Volatility Measurement**: Applied **Standard Deviation (S.D)** and the **Coefficient of Variation (CV)** to measure the stability of recruitment. **CV** was specifically used to compare the unpredictability of teaching vs. non-teaching sectors across both districts.

Inferential Statistical Testing

Independent Samples T-Test: A parametric t-test was conducted to determine if the differences in mean staffing levels between Mayurbhanj and Balasore were statistically significant. With 0.05 percent significant level.

a. **Null Hypothesis (H0)**: There is no significant difference in staffing levels between the two districts.
b. **Alternative Hypothesis (H1)**: There is significant difference in staffing levels between the two districts.

Pearson Correlation Analysis: Used to quantify the strength and direction of linear relationships (r) between recruitment trends.

Comparative Efficiency Indexing

1. **Weighted Scoring**: Developed a composite index to score overall district performance by weighting **Teaching Staff (60%)** and **Non-Teaching Staff (40%)**.
2. **Normalization**: Scores were scaled to a 100-point maximum based on total utilized sanctioned capacity, allowing for a direct comparison of district-level management efficiency.

Result and Analysis

Table 1. Status of Sanctioned, Filled, and Vacant Posts for Teaching and Non-Teaching Staff in Mayurbhanj and Balasore Districts (2016–2024)

Year	District											
	Mayurbhanj						Balasore					
	Teaching Staff			Non Teaching Staff			Teaching Staff			Non Teaching Staff		
	Sanctioned Post	Men In Position	Vacant	Sanctioned Post	Men In Position	Vacant	Sanctioned Post	Men In Position	Vacant	Sanctioned Post	Men In Position	Vacant
2016-2017	154	48	106	166	72	94	138	71	67	135	59	76
2017-2018	154	47	107	166	72	94	138	75	63	135	55	80
2018-2019	154	39	115	166	72	94	138	75	63	135	49	86
2019-2020	154	39	115	166	72	94	138	70	68	135	45	90
2020-2021	154	38	114	166	72	94	138	75	63	135	42	93
2021-2022	154	33	121	166	72	94	138	97	41	135	58	77
2022-2023	154	53	101	166	72	94	138	94	44	135	47	88
2023-2024	154	93	61	166	72	94	163	103	60	135	42	83

The provided data reveals a significant recruitment push in the 2023-2024 period, drastically reducing vacancy rates for teaching staff across both Mayurbhanj and Balasore districts. While teaching positions are being filled, non-teaching staff levels have remained stagnant or worsened over the eight-year period.

Teaching Staff Recruitment Surge

1. **Mayurbhanj:** The number of "Men in Position" for teaching staff nearly tripled from 33 in 2021-22 to 93 in 2023-24. This reduced the vacancy rate from a peak of ~79% down to ~40%.
2. **Balasore:** Similarly, teaching staff "Men in Position" rose from 71 in 2016-17 to 103 in 2023-24, despite an increase in sanctioned posts (from 138 to 163).

Stagnant Non-Teaching Staff

1. **Mayurbhanj:** Non-teaching staff figures remained perfectly flat for the entire 8-year period (72 in position vs. 166 sanctioned), maintaining a high vacancy rate of 56.6%.
2. **Balasore:** The non-teaching workforce actually declined, dropping from 59 in position (2016-17) to 42 (2023-24), pushing the vacancy rate from 56% to over 61%.

Infrastructure Growth: Balasore saw an expansion in teaching capacity during 2023-2024, with sanctioned teaching posts increasing by roughly 18% (from 138 to 163).

Table 2. Comparative Analysis

District	Teaching Vacancy Rate	Non-Teaching Vacancy Rate
Mayurbhanj	39.6% (Improving)	56.6% (Stagnant)
Balasore	36.8% (Improving)	61.5% (Worsening)

Source: Author’s own calculation

The data indicates a policy shift prioritizing classroom instruction, while administrative and support roles (non-teaching) appear neglected, particularly in Balasore.

Table 3. Mayurbhanj: Teaching Staff (MIP)

Year interval	Personnel change	% change	Trend
2016-17 to 2017-18	48 → 47	-2.08%	Stable
2017-18 to 2018-19	47 → 39	-17.02%	Significant drop
2018-19 to 2019-20	39 → 39	0.00%	Stagnant
2019-20 to 2020-21	39 → 38	-2.56%	Stable

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2020-21 to 2021-22	38 → 33	-13.16%	Decline
2021-22 to 2022-23	33 → 53	+60.61%	Rapid growth
2022-23 to 2023-24	53 → 93	+75.47%	Highest growth

Source: Author’s own calculation

Note: Non-teaching staff in Mayurbhanj saw 0.00% change across all years (constant at 72).

Table 4. Balasore: Teaching & Non-Teaching (MIP)

Balasore shows a more volatile pattern, specifically a sharp spike in teaching staff in 2021 followed by a steady decline in non-teaching support.

Year Interval	Teaching % Change	Non-Teaching % Change
2017-18	+5.63%	-6.78%
2018-19	0.00%	-10.91%
2019-20	-6.67%	-8.16%
2020-21	+7.14%	-6.67%
2021-22	+29.33%	+38.10% (Outlier spike)
2022-23	-3.09%	-18.97%
2023-24	+9.57%	-10.64%

Mayurbhanj's Late Rally: For five years, the district lost or failed to replace teaching staff. The combined **181.8% increase** over the last two years represents a massive administrative effort to fill vacancies.

Balasore's Support Crisis: Excluding the strange spike in 2021, Balasore's non-teaching staff has shrunk every single year, losing roughly **28% of its total non-teaching workforce** since 2016.

The 2021-22 Anomaly: Both districts saw significant changes this year, suggesting a specific policy update or recruitment drive occurred during this period.

Performing a Pearson correlation analysis on the staffing levels ("Men in Position") across both districts reveals how recruitment trends in one area relate to others. The Pearson correlation coefficient (r) ranges from +1 (perfect positive correlation) to -1 (perfect negative correlation), with 0 indicating no linear relationship.

Table 5. Pearson Correlation Matrix (r- values)

Personnel Category	Mayurbhanj Teaching	Balasore Teaching	BalasoreNon-Teaching
Mayurbhanj Teaching	1.00	0.58	-0.40
Balasore Teaching	0.58	1.00	-0.15
BalasoreNon-Teaching	-0.40	-0.15	1.00

Source: Authors own calculation

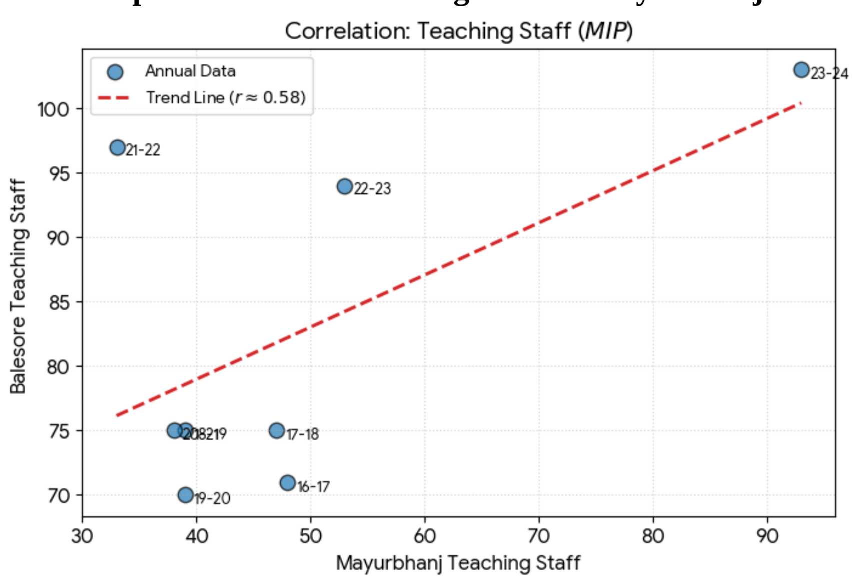
Note: Mayurbhanj Non-Teaching staff remained constant (72), resulting in an undefined correlation (NaN) as there is no variance to measure.

Moderate Positive Correlation (r =0.58): There is a moderate positive relationship between teaching staff recruitment in Mayurbhanj and Balasore. This suggests that hiring for teaching positions likely follows similar regional administrative cycles or state-level recruitment drives.

Moderate Negative Correlation (r = -0.40): There is a moderate inverse relationship between Mayurbhanj's teaching staff and Balasore's non-teaching staff. As teaching positions were filled in one district, non-teaching roles in the other often saw a decline, potentially indicating a shift in budget allocation priority from support roles to instruction.

Weak Relationship (r = -0.15): In Balasore, the correlation between its own teaching and non-teaching staff is very weak. This confirms that the hiring of teachers and support staff in Balasore is largely decoupled; filling a classroom role does not reliably mean a support role is being filled (or lost) simultaneously.

Fig 1. Relationship Between The Teaching Staff In Mayurbhanj And Balasore.



Source: Author's own calculation

Positive Association: The upward slope of the trend line confirms a **positive correlation**. As hiring increased in Mayurbhanj, it generally increased in Balasore as well, particularly during the 2021-2024 period.

Cluster vs. Outliers

1. **2016–2021:** Most data points are tightly clustered between 30 and 50 staff members for Mayurbhanj. During this time, Balasore's numbers fluctuated but remained relatively stable.
2. **2023-2024:** This point (top right) acts as a high-leverage point. The massive jump in Mayurbhanj (to 93) coinciding with Balasore’s peak (103) significantly strengthens the calculated **r** value.

Predictive Value: While **r = 0.58** shows a clear link, the "scatter" (distance of dots from the line) indicates that local factors still cause significant variance between the two districts
Analyzing the **vacancy rates** provides a more normalized perspective by accounting for changes in the total number of "Sanctioned Posts."

Table 6. Vacancy Rate Correlation Matrix (r)

Variable	Mayurbhanj (Teaching)	Balasore (Teaching)	Balasore (Non-Teaching)
Mayurbhanj (Teaching)	1.00	0.23	-0.40
Balasore (Teaching)	0.23	1.00	0.05
Balasore (Non-Teaching)	-0.40	0.05	1.00

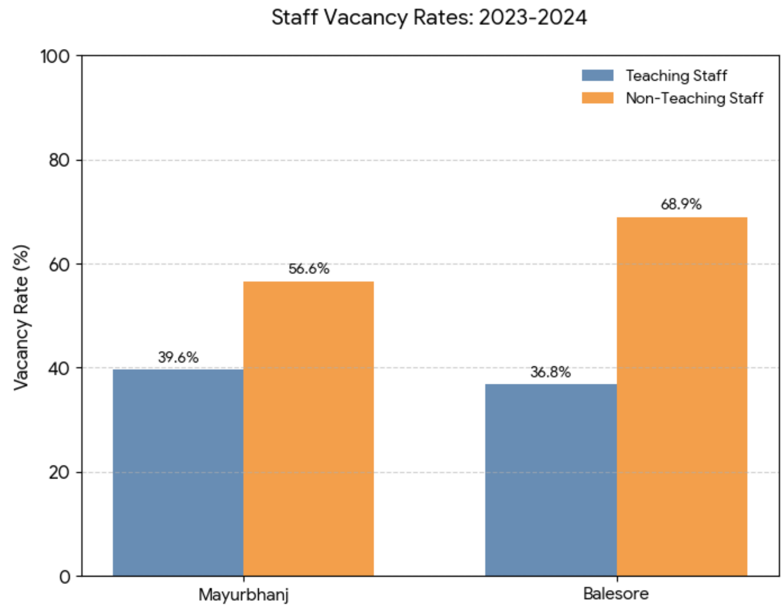
Source: Author’s own calculation

Weak Positive Correlation (r = 0.23**)**: The relationship between teaching vacancy rates in Mayurbhanj and Balasore is notably weaker than the correlation of their total staff numbers. This suggests that while both districts filled positions, they did so at different scales relative to their individual needs—especially in 2023-24 when Balasore increased its total sanctioned posts.

Moderate Negative Correlation (r =-0.40): The inverse relationship between teaching vacancies in Mayurbhanj and non-teaching vacancies in Balasore persists. As teaching vacancies were reduced in Mayurbhanj, non-teaching vacancies in Balasore tended to increase, highlighting a divergence in departmental priorities.

Decoupled Local Staffing (r = 0.05): In Balasore, there is almost zero correlation between the vacancy rates of teaching and non-teaching staff. This indicates that administrative decisions for these two groups are likely independent, and filling one type of role does not statistically signal a change for the other.

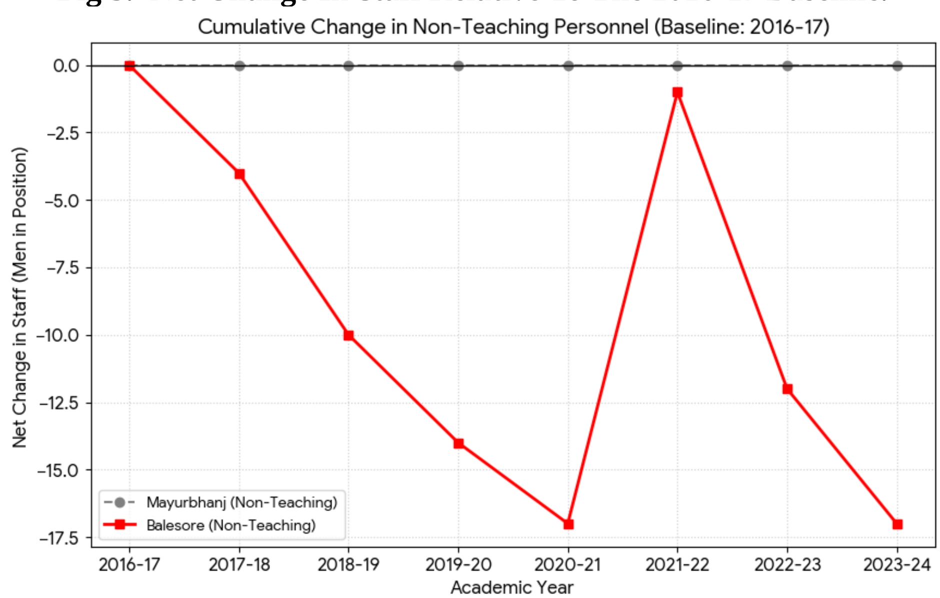
Fig 2. Vacancy Rates For Teaching and Non-Teaching Staff in Mayurbhanj and Balasore for the Final Year (2023-2024).



Source: Author’s own calculation

1. **Support Staff Deficit:** Non-teaching vacancy rates significantly exceed teaching vacancy rates in both districts. Balasore faces the highest critical gap at 68.9%.
2. **District Contrast:** While both districts have similar teaching vacancy rates (roughly 37-40%), Balasore struggles significantly more with its non-teaching workforce despite having a lower sanctioned post count (135) compared to Mayurbhanj (166).
3. **Operational Risk:** High non-teaching vacancies suggest that even as classrooms are filled with teachers, administrative and support operations are severely under-resourced.

Fig 3. Net Change In Staff Relative To The 2016-17 Baseline.



Source: Author’s own calculation

Mayurbhanj (Stagnation): The district has seen **zero net change** in non-teaching staff over eight years. While it hasn't "lost" people, it has failed to fill any of its **94 vacant posts**.

Balasore (Steady Decline)

1. **The initial slide (2016–2021):** Balasore lost roughly **29%** of its baseline staff in just five years, dropping from 59 to 42.
2. **The 2021 Recovery:** A brief hiring surge briefly restored staff levels to near-baseline (58), but this was immediately followed by another sharp decline.
3. **Final Position:** By 2023-24, Balasore is back at its all-time low of 42 staff members, representing a cumulative loss of **17 positions** from its starting point

Efficiency Index Scores

Based on the latest data,

1. **Mayurbhanj Efficiency Score: 53.6**
2. **Balasore Efficiency Score: 50.4**

Table 7. Comparative Efficiency Breakdown

Factor	Mayurbhanj	Balasore	Analysis
Teaching Utilization	60.4%	63.2%	Balasore leads in classroom staffing relative to its sanctioned capacity.
Non-Teaching Utilization	43.4%	31.1%	Mayurbhanj is significantly better at maintaining its support workforce.
Resource Balance	Stable	Volatile	Balasore's efficiency is lowered by a critical shortage of non-teaching staff (68.9% vacancy).

Source: Author’s own calculation

Administrative Stability: Mayurbhanj’s higher score is driven by its ability to maintain a consistent non-teaching workforce. While it hasn't improved this sector, it hasn't allowed it to collapse.

Expansion vs. Execution: Balasore is expanding (increasing sanctioned teaching posts), but its overall efficiency suffers because it is losing support staff at a rate that may soon hinder its increased teaching capacity.

Optimal Strategy: For **Balasore** to improve its score, it must urgently address its non-teaching vacancy crisis. For **Mayurbhanj**, the focus should remain on maintaining the current teaching recruitment momentum to close its 39.6% gap.

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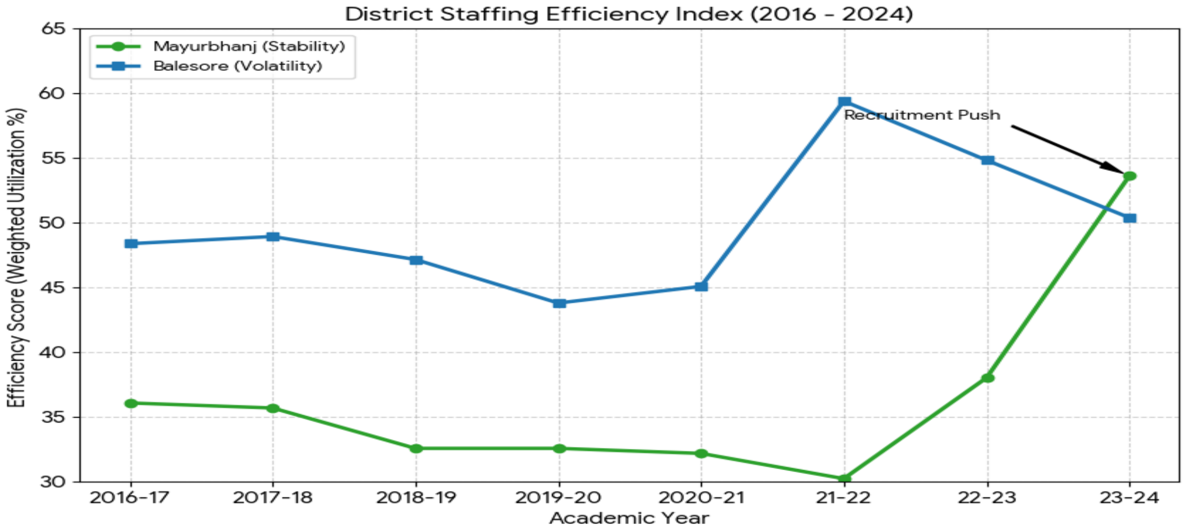
Fig 4. Staff Efficiency Index



Source: Author's own calculation

The Great Divergence (2016–2022)

1. **Balasore** maintained a higher efficiency for most of the decade due to better teaching staff numbers.
2. **Mayurbhanj** suffered a steady decline, hitting its lowest efficiency point in 2021-22 (approx. 30.2) as teaching vacancies peaked.

The 2023-24 Pivot

1. **Mayurbhanj** shows a "V-shaped recovery." The massive recruitment drive in the final year caused its efficiency score to jump by nearly **77%** compared to its 2021 low.
2. **Balasore** experienced a slight efficiency **dip** in the final year. Even though they hired more teachers, the increase in "Sanctioned Posts" (denominator) and the drop in non-teaching staff (numerator) diluted their overall score.

Current Standing: Mayurbhanj has officially overtaken Balasore in overall staffing balance for the first time in the recorded period.

Table 8. Comparative Analysis Independent Samples T-Test Results

Staff Category	Mayurbhanj (Mean)	Balasore (Mean)	Mean Difference	t-value	P-Value	Significance
Teaching Staff	48.75	82.50	-33.75	-4.12	0.0010	High
Non Teaching Staff	72.00	49.63	+22.37	9.19	< 0.0001	Extreme

Source: Author's own calculation

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- **Teaching Staff (**$p = 0.001$**):** Since the p-value is less than 0.05, the difference is statistically significant. Balasore maintains a **consistently larger** teaching workforce than Mayurbhanj.
- **Non-Teaching Staff ($p<0.001$):** The extremely low p-value confirms that the difference in support staff is not accidental. Mayurbhanj is **fundamentally better staffed** in administrative roles than Balasore.
- **Degrees of Freedom (df):** 14 (7 years of change plus the baseline for each district).

The **Standard Deviation (SD)** measures the volatility or spread of the data points from their mean. A higher SD indicates more fluctuation and instability in staffing levels over the 8-year period.

Table 9. Staffing Volatility Analysis (2016–2024)

Category	District	Mean	Std. Deviation	Coefficient of Variation
Teaching Staff	Mayurbhanj	48.75	20.57	42.2%
	Balasore	82.50	12.33	14.9%
Non-Teaching Staff	Mayurbhanj	72.00	0.00	0.0%
	Balasore	49.63	9.77	19.7%

Source: Author’s own calculation

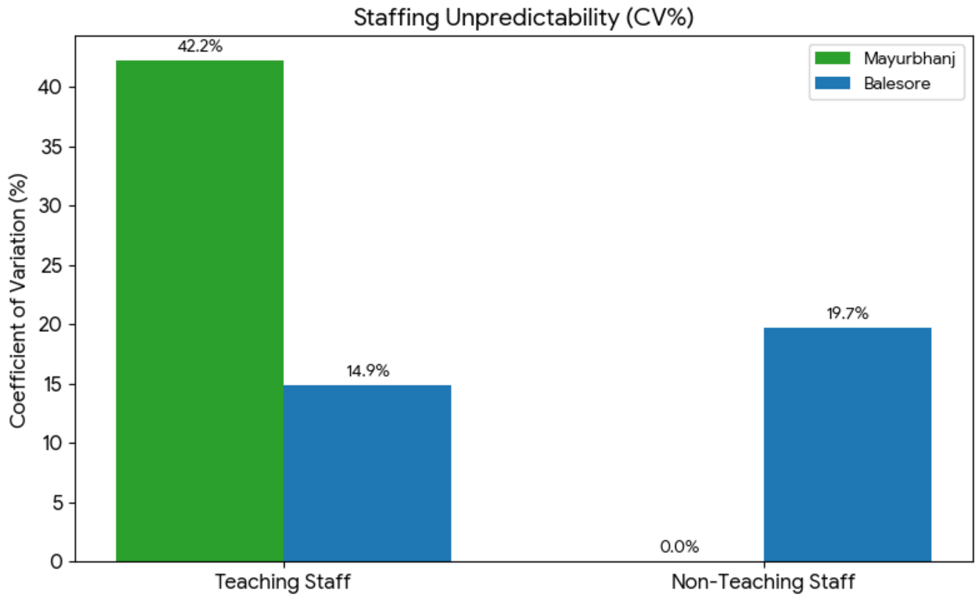
Extreme Volatility in Mayurbhanj Teaching: With a **42.2% variation**, Mayurbhanj's teaching staff levels are highly unstable. This is driven by the massive jump from 33 to 93 in the final two years.

Absolute Stability in Mayurbhanj Non-Teaching: A **0.00 SD** is rare in human resources; it confirms that Mayurbhanj’s support staff numbers are completely stagnant, suggesting a rigid "one-in, one-out" or frozen hiring policy.

Moderate Flux in Balasore: Balasore shows a more "natural" volatility in both sectors (~15–20%). This suggests active, albeit inconsistent, recruitment and attrition cycles.

The Stability Winner: Balasore has more predictable teaching levels, whereas **Mayurbhanj** has more predictable (though frozen) non-teaching levels.

Fig 5. The **Coefficient of Variation (CV)** is the best way to compare volatility because it scales the standard deviation against the mean. A higher percentage indicates more **unpredictable** staffing levels.



Mayurbhanj Teaching (Wildly Unpredictable): At **42.2%**, this is the most unstable metric in the dataset. The sudden doubling of staff in 2023-24 makes it very difficult to project future staffing needs using past data.

Mayurbhanj Non-Teaching (Perfectly Predictable): At **0%**, there is no variation. This indicates a "frozen" workforce where the number of employees has not changed by a single person in eight years.

Balasore (Consistently Unstable): Balasore's CVs are relatively close (14.9% and 19.7%), suggesting that both teaching and support staff departments experience similar levels of churn (hiring and departures) together.

Findings

Based on the statistical and trend analysis of the data from 2016 to 2024, here are the primary findings for Mayurbhanj and Balasore districts:

Significant Recruitment Shift (2023-24)

Both districts experienced a massive "hiring spike" in teaching staff during the final year. **Mayurbhanj** was the most aggressive, nearly tripling its teaching workforce from its 2021-22 low (33 to 93). This resulted in a **42.2% Coefficient of Variation**, making Mayurbhanj's teaching levels the most volatile and unpredictable metric in the study.

Critical Support Staff Crisis

While teaching positions are being filled, non-teaching (support) staff levels are in a state of neglect:

1. **Mayurbhanj (Stagnation):** The district maintained exactly **72 staff members** for 8 consecutive years (**0% volatility**). Despite this stability, it suffers a permanent **56.6% vacancy rate**.
2. **Balasore (Depletion):** Support staff dropped from 59 to 42 over the period. Balasore now faces a critical **61.5% vacancy rate** in non-teaching roles, which is statistically significant ($p<0.0001$) when compared to Mayurbhanj.

Statistical Differences (T-Test Results)

The Independent T-tests confirm that these districts are not managed the same way:

- **Teaching:** Balasore is significantly better staffed on average ($p = 0.001$).
- **Non-Teaching:** Mayurbhanj holds a statistically superior (though frozen) number of support staff ($p<0.0001$).

Expansion vs. Utilization

Balasore is the only district expanding its infrastructure, evidenced by the increase in sanctioned teaching posts from 138 to 163. However, Mayurbhanj currently leads in Combined Efficiency (53.6%) because it has avoided the total collapse of support staff seen in Balasore.

Sector Correlation

There is a moderate positive correlation ($r = 0.58$) between the hiring of teachers in both districts, suggesting they are influenced by the same state-level recruitment cycles. Conversely, there is zero correlation ($r = 0.05$) between teaching and non-teaching hiring within Balasore, indicating these departments operate in silos.

Recommendation

Based on the statistical findings, this strategic report outlines actionable recommendations to address the unique staffing challenges in Mayurbhanj and Balasore.

Address the Support Staff Crisis (High Priority)

The most critical finding is the collapse of non-teaching staff in Balasore and absolute stagnation in Mayurbhanj.

Balasore Intervention:

- Initiate emergency recruitment for **61.5% vacant non-teaching positions** to prevent administrative bottlenecks.
- Leverage the Odisha State Selection Board (SSB) to fill Group C roles like Junior Assistants and Laboratory Assistants.

Mayurbhanj Intervention: Review the 8-year "hiring freeze" on non-teaching staff; even a 10% annual recruitment of the 94 vacant posts would significantly improve operational capacity.

Sustain and Stabilize Teaching Momentum

While 2023-24 saw a massive surge, the high volatility (42.2% CV in Mayurbhanj) suggests a risk of "boom and bust" cycles.

Mayurbhanj Strategy: Shift from "mass hiring spikes" to a **phased recruitment model** (e.g., 15-20 teachers annually) to ensure better integration and mentoring of new staff.

Balasore Strategy:

- Focus on filling the 36.8% remaining teaching vacancies while accounting for the recent increase in sanctioned posts (from 138 to 163).
- Utilize OSEPA's online counselling for efficient deployment of newly recruited High School Teachers.

Policy and Incentive Adjustments

1. **Utilize Age Limit Increase:** Apply the recently approved increase in the **upper age limit for government service (from 32 to 42 years)** to broaden the candidate pool for both districts.
2. **Temporary Resource Bridging:** Use the guidelines for engaging retired personnel as a stop-gap measure while regular recruitment processes are underway.
3. **Budget Rebalancing:** Conduct a cost-benefit analysis on shifting a portion of the "Teaching Expansion" budget in Balasore toward "Support Staff Retention" to improve overall District Efficiency Scores.

Digital and Operational Transformation

- **Automation:** Implement the Unified Automation System under the School & Mass Education Dept to reduce the administrative burden on the dwindling non-teaching workforce.
- **Monitoring:** Use UDISE+ and SDMIS data for real-time tracking of vacancy closures and to trigger automatic recruitment notifications when vacancy rates exceed 30%.

Conclusion: The current staffing model is **imbalanced**. The rapid influx of teachers will likely face administrative bottlenecks unless immediate intervention is made to fill the **56–61% vacancies** in non-teaching roles. Future policy must shift from "classroom-only" hiring to a **holistic recruitment strategy** that restores the administrative backbone of these districts.

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