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Organizational Classification of HR Analytics Maturity: Evidence from Service Sector Organizations in India

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ABSTRACT

HR analytics is essential for data-driven decision-making in modern enterprises. Although HR analytics is becoming more important, firms vary in their adoption and maturity. This research classifies Indian service sector firms by analytics capability and supporting organizational elements to assess HR analytics maturity. HR professionals and managers completed a standardized questionnaire for a quantitative cross-sectional study. The service industry, notably healthcare and hospitals, provided 112 valid responders. The study identified homogenous HR analytics-related firms using descriptive statistics, reliability analysis, and cluster analysis. From basic operational use to advanced strategic and predictive applications, the data show diverse organizational clusters for HR analytics maturity. The findings also show that organizational support, technology infrastructure, and data-driven culture improve analytics maturity and organizational outcomes. The report adds to HR analytics literature and helps managers and HR practitioners enhance workforce decision-making by understanding HR analytics adoption patterns.

Keywords : HR analytics adoption, Cluster analysis, Organizational efficiency, Organizational Support.

Introduction:

Digital technology and organizational data have rapidly changed human resource management approaches across sectors. Data-driven decision-making improves workforce management and organizational performance, and organizations are realizing this. Human Resource (HR) analytics, also known as people analytics or workforce analytics, is a key management tool that helps firms evaluate personnel data and make strategic decisions (Marler & Boudreau, 2017). HR analytics supports recruiting, employee engagement, performance management, and workforce planning using statistical methods, predictive modeling, and data visualization. In a data-driven corporate climate, HR analytics use has increased globally as companies seek to stay competitive. Analytics-based HR solutions have helped Google, IBM, and Microsoft detect talent tendencies, anticipate employee churn, and boost productivity. Research shows that HR analytics help organisations integrate human resource plans with organisational goals and increase performance (Davenport & Harris, 2007; Levenson, 2018). Recent studies also show that HR analytics may turn HR departments into strategic business partners that drive innovation and performance (Minbaeva, 2018; Margherita, 2021).
HR analytics are being used to support evidence-based HR management, according to recent research. Analytics-driven HR methods may uncover employee behaviour trends and improve talent management initiatives, according to academics (Huselid & Becker, 2021). Wamba et al. (2021) underline that big data analytics can improve organizational performance and decision-making. Recent empirical research demonstrates that advanced analytics methods boost worker productivity, employee engagement, and operational efficiency (Sharma & Sharma, 2023; Tursunbayeva et al., 2022). HR analytics is now seen as a strategic competency that improves worker outcomes and sustains competitive advantage. HR analytics adoption is variable across enterprises and countries, despite its potential benefits. Lack of analytical capacity, technology infrastructure, and management support lead many organisations to use intuition-based HR decision-making (Angrave et al., 2016). Even with analytics technologies, HR managers may struggle to analyze complicated data and turn insights into meaningful plans. These constraints show that HR analytics deployment requires technology tools, organizational support, and a data-driven culture (Minbaeva, 2018).

Indian enterprises are interested in HR analytics due to the focus on digital transformation and data-driven management. Indian service industries including information technology, healthcare, financial services, and education are growing quickly, requiring improved labor management strategies. Recent industry reports and empirical research show that many Indian organisations are investing in HR analytics platforms and HR information systems to increase talent acquisition, employee engagement, and workforce planning (Sarkar & Searcy, 2023). The use of HR analytics in India is still evolving, with many firms missing the analytical ability and organizational infrastructure to properly exploit worker data. The maturity and efficiency of HR analytics integration vary greatly among enterprises. HR analytics is important for organizational success, yet there are gaps in the literature. First, much HR analytics research has concentrated on developed nations and large multinational firms, with little empirical data from emerging economies. Second, most research have focused on causal correlations between HR analytics adoption and organizational performance outcomes, rather than identifying organizational profiles based on analytics maturity and support.

2. Literature Review

2.1 HR Analytics and Data-Driven Human Resource Management

The increasing significance of data-driven decision-making has profoundly altered human resource management techniques in modern enterprises. HR analytics denotes the methodical use of workforce data, statistical analysis, and predictive modeling to facilitate strategic HR decisions and enhance corporate performance (Marler & Boudreau, 2017). In contrast to conventional HR methods that depend significantly on management intuition and experience, HR analytics allows firms to extract actionable insights from employee data and synchronize human capital plans with corporate goals.

The notion of HR analytics has progressed in tandem with the growing accessibility of digital data and analytical instruments. Davenport and Harris (2007) asserted that firms that proficiently employ analytics get a competitive edge by making better informed, evidence-based choices. Angrave et al. (2016) contended that HR analytics may convert the HR function from an administrative support role into a strategic partner that can impact organizational outcomes. Workforce analytics enables firms to discern patterns about employee performance, retention, engagement, and productivity, facilitating enhanced workforce planning and decision-making.

Notwithstanding its prospective advantages, the use of HR analytics is inconsistent among enterprises. Numerous firms encounter obstacles concerning data quality, analytical proficiency, and managerial preparedness, which hinder the efficient application of HR analytics in practice (Boudreau & Cascio, 2017). As a result, the degree of analytics adoption differs significantly among industries and companies, necessitating an analysis of how various entities incorporate analytics into their HR operations.

2.2 HR Analytics and Organizational Efficiency

One of the most extensively examined results of HR analytics is its capacity to enhance organizational efficiency and performance. The research on strategic human resource management indicates that successful HR practices substantially enhance company productivity and competitive advantage (Becker & Huselid, 2006; Huselid, 1995). HR analytics enhances this connection by allowing firms to assess the efficacy of HR efforts and implement evidence-based enhancements.

Numerous studies emphasize the significance of HR analytics in enhancing worker results. Levenson (2018) contends that workforce analytics enables firms to comprehend the determinants of employee success and synchronize HR policies with business goals. Rasmussen and Ulrich (2015) assert that analytics-driven HR decision-making enhances workforce planning, talent management, and employee development procedures. Through the analysis of personnel data, firms may discern inefficiencies, optimize talent distribution, and execute targeted interventions to enhance productivity and engagement.

Moreover, predictive analytics methodologies empower firms to foresee prospective labor issues, such staff attrition or skill deficiencies. Davenport, Harris, and Shapiro (2010) shown that firms employing personnel analytics may more accurately forecast employee attrition and design retention strategies that mitigate turnover expenses. These skills enhance organizational efficiency by accelerating decision-making and increasing accuracy, while simultaneously minimizing operational inefficiencies.

2.3 Organizational Support for HR Analytics Implementation

The effective deployment of HR analytics primarily hinges on the extent of organizational assistance provided. Organizational support denotes the institutional and cultural factors that facilitate the efficient implementation of analytics efforts inside a business. The prerequisites encompass leadership dedication, technology infrastructure, analytical proficiency, and a culture that prioritizes data-driven decision-making (Falletta, 2014).

Leadership support is crucial for facilitating the use of analytics. When upper management actively endorses analytics projects, firms are more inclined to allocate essential resources and incorporate analytics into strategic decision-making processes (Minbaeva, 2018). Likewise, technology infrastructure, including HR information systems and data management platforms, establishes the essential foundation for the collection, analysis, and interpretation of worker data.

The organizational culture significantly impacts the efficacy of HR analytics deployment. A culture that promotes evidence-based decision-making and analytical reasoning allows HR professionals to leverage analytics insights more efficiently (Rasmussen & Ulrich, 2015). In the absence of such a culture, analytics tools may be present inside the business yet remain underutilized owing to opposition to change or insufficient analytical skills.

2.4 HR Analytics Maturity and Organizational Segmentation

Recent study indicates that firms vary considerably in their HR analytics maturity. HR analytics maturity is the degree to which firms incorporate analytics into HR operations and leverage data-driven insights for strategic decision-making. Certain firms utilize sophisticated predictive analytics and incorporate analytics into strategic planning, whilst others depend only on descriptive reporting or fundamental HR indicators (Levenson, 2018). Comprehending these distinctions is crucial for recognizing trends in analytics usage among firms. Cluster analysis has been employed in several management studies to categorize businesses into groups according to analogous qualities or behavioral patterns (Hair et al., 2019). By finding clusters of firms exhibiting analogous degrees of analytics adoption, support infrastructure, and efficiency outcomes, researchers may get a deeper comprehension of the phases of analytics maturity present within a certain sector or area.

In the realm of HR analytics, segmentation methodologies can discern firms exhibiting sophisticated analytical skills from those in the nascent phases of adoption. This investigation offers critical insights into the variances in organizational analytics utilization and the elements that facilitate successful analytics deployment.

2.5 Research Gap

While current research underscores the strategic significance of HR analytics in enhancing organizational performance, the majority of the literature concentrates on developed economies and big multinational corporations. Empirical research on the uptake of HR analytics in emerging economies, especially in regional service industries, is scarce. Moreover, the majority of previous studies focus on the causal linkages between HR analytics and organizational performance, but there is a paucity of research examining how businesses may be categorized into diverse profiles depending on their analytics maturity.

This research investigates the use of HR analytics in service sector firms in Gujarat, India, therefore addressing existing gaps. The study utilizes cluster analysis to delineate certain organizational groups based on the adoption of HR analytics, organizational support, and efficiency outcomes. This segmentation-based methodology enhances comprehension of the variability in HR analytics maturity among firms and furnishes actionable recommendations for entities aiming to bolster their analytics proficiency.

3.1 Research Objective:

The growing utilization of HR analytics has revolutionized human resource management by allowing firms to make data-informed choices on recruiting, employee performance, retention, and workforce planning. The degree of analytics adoption and its resultant effects significantly range among firms due to variations in technology infrastructure, leadership endorsement, and organizational culture. Instead of presuming universal adoption trends, it is crucial to recognize specific organizational profiles that demonstrate differing degrees of HR analytics maturity.

The main aim of this study is to identify and evaluate certain organizational clusters based on HR analytics adoption, organizational support, and efficiency outcomes within the service industry in Gujarat. The research used cluster analysis to categorize firms into distinct divisions based on varying degrees of analytics integration and performance results.

3.2 Research Objectives :

- To identify unique organizational clusters based on the adoption of HR analytics, levels of organizational support, and measures of organizational efficiency.
- To analyze the variations in HR analytics procedures among the specified groupings.
- To examine the traits of firms exhibiting elevated degrees of HR analytics sophistication.

3.3 Research Questions:

To achieve the objectives of the study, the following research questions are addressed:

RQ1: What distinct organizational clusters exist in the service sector based on HR analytics adoption, organizational support, and organizational efficiency?

RQ2: How do HR analytics practices vary across the identified clusters?

RQ3: Which organizational factors differentiate high analytics maturity organizations from moderate or low analytics adoption groups?

4 Research Methodology:

4.1 Research Design

This study used a quantitative cross-sectional research approach to investigate the trends of HR analytics adoption and organizational effectiveness in service sector businesses in Gujarat. The main goal is to delineate unique organizational profiles based on the use of HR analytics, organizational support, and efficiency results. Cluster analysis was utilized as the primary analytical method to categorize companies into homogenous groups with analogous traits.
The research used a survey methodology to get standardized responses from HR experts and managerial staff across several service sectors.

4.2 Sample and Data Collection

Primary data were obtained via a structured questionnaire distributed to HR experts and managerial personnel employed in service sector firms in Gujarat. The targeted sectors were concentrated on healthcare and the hospital industry. A stratified sampling method was employed to guarantee participation from various service sectors. Initially, 150 responses were gathered via online and offline survey methodologies. Following the screening of data for incomplete responses and discrepancies, 112 valid replies were preserved for final analysis. The respondents were experts engaged in HR functions, management decision-making, and organizational operations, offering insights on HR analytics methods and organizational efficacy.

4.3 Measurement Instrument

This study employed a structured questionnaire to assess the degree of HR analytics adoption, organizational support, and organizational efficiency in service sector businesses. The questionnaire was designed following a comprehensive examination of existing literature on HR analytics, data-driven human resource management, and organizational performance (Angrave et al., 2016; Marler & Boudreau, 2017; Rasmussen & Ulrich, 2015). The questionnaire was developed to assess the attitudes of HR professionals and management personnel concerning the utilization of HR analytics and its effects on organizational results.
The questionnaire had two sections. The initial segment gathered demographic data, encompassing respondents' sector membership, occupational function, and years of professional experience. These factors were used to furnish contextual insight into the respondents and guarantee representation across various service sectors.
The second segment had 22 assessment questions reflecting three fundamental constructs: HR Analytics Adoption (HRAA), Organizational Efficiency (ORE), and Organizational Support (ORS). All items were evaluated on a five-point Likert scale, from 1 (Strongly Disagree) to 5 (Strongly Agree). The Likert scale method is extensively employed in organizational research to assess attitudes, perceptions, and behavioral inclinations in a uniform and standardized fashion (Hair et al., 2019).

HR Analytics Adoption

HR Analytics Adoption denotes the degree to which firms employ analytical tools and data-driven methodologies to enhance HR decision-making processes. The idea signifies the shift from intuition-driven human resource methods to evidence-based workforce management (Davenport et al., 2010; Marler & Boudreau, 2017). The concept was assessed using ten elements (HRAA1–HRAA10) that reflect the operational and strategic integration of analytics into HR operations.

The items evaluate the extent to which firms utilize analytics in recruiting, employee performance monitoring, predicted attrition analysis, and the identification of training requirements. Supplementary elements assess the integration of HR analytics into strategic planning, the utilization of dashboards or HR analytics software by organizations, the assignment of dedicated personnel for HR analytics, and the extent to which HR decisions are increasingly informed by data rather than managerial intuition. These factors jointly signify the extent of analytics integration inside human resource activities.

Organizational Efficiency

Organizational Efficiency denotes the performance results linked to the proficient utilization of HR analytics inside a business. Prior research indicates that HR analytics may boost worker efficiency, increase employee engagement, and improve organizational performance through data-driven decision-making (Angrave et al., 2016; Rasmussen & Ulrich, 2015).

This concept was assessed using eight questions (ORE1–ORE8) that gauge perceived enhancements in employee productivity, retention, absenteeism reduction, decision-making velocity, employee engagement, workforce planning precision, overall organizational performance, and operational efficiency. These indicators together reflect the role of HR analytics in the effective deployment of human resources inside enterprises.

Organizational Support

Organizational Support denotes the institutional and structural circumstances that enable the execution of HR analytics efforts. Previous studies demonstrate that leadership commitment, technology infrastructure, and an organizational culture that prioritizes data-driven decision-making are essential facilitators of analytics adoption (Falletta, 2014; Marler & Boudreau, 2017). The construct was evaluated through four items (ORS1–ORS4) that examine the degree of organizational leadership support for HR analytics initiatives, the adequacy of technological infrastructure for analytics activities, the promotion of a data-driven culture, and the allocation of sufficient budget for HR analytics initiatives. These characteristics collectively signify the organizational preparedness necessary for the effective execution of analytics-driven HR strategies. The measuring items included in this study were derived from known literature on HR analytics, strategic human resource management, and organizational performance, and were tailored to suit the context of service sector firms in Gujarat. Before data collection, the questionnaire was evaluated to confirm the clarity and pertinence of the items for responders.

Data Analysis and Results

This section presents a comprehensive statistical analysis to examine the relationship between HR analytics adoption and organizational efficiency in service sector organizations in Gujarat. Both descriptive and inferential statistical techniques were employed to test the proposed hypotheses and address the research objectives.

DEMOGRAPHIC		Frequency	Percent
SECTOR	IT	29	25.9
	Healthcare	33	29.5
	Education	20	17.9
	Financial services	16	14.3
	Other	14	12.5
OCCUPATION	student	17	15.2
	Job	88	78.6
	Profession	7	6.3
EXPERIENCE	0-5 years	83	74.1
	6-10 years	21	18.8
	11-15-years	2	1.8
	16-20 years	3	2.7
	above 20 years	3	2.7
Total		112	100.0

CROSS TABULATIONS:

SECTOR * EXP Crosstabulation							
		EXP					Total
		0-5 years	6-10 years	11-15-years	16-20 years	above 20 years	
SECTOR	IT	24	5	0	0	0	29
	Healthcare	26	3	1	2	1	33
	Education	14	3	0	1	2	20
	Financial services	11	4	1	0	0	16
	Other	8	6	0	0	0	14
Total		83	21	2	3	3	112

The cross-tabulation of sector and experience reveals that the sample mostly consists of early-career professionals, with 74.1% (83 out of 112 respondents) possessing 0–5 years of experience across all sectors. The Healthcare sector has the most presence with 33 respondents, followed by IT with 29 respondents, Education with 20 respondents, Financial Services with 16 respondents, and Other sectors with 14 respondents. The majority of respondents across all sectors possess 0–5 years of experience, with minimal representation in higher experience categories, totalling only 8 respondents with over 10 years of experience. Healthcare and Education have minor variance in experience levels, but industries like IT, Financial Services, and Others predominantly consist of lower experience categories. The distribution indicates a significant bias towards less experienced professionals, potentially affecting the interpretation and generalizability of the study's conclusions.

Chi-Square Tests			
	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	19.728[a]	16	0.233
Likelihood Ratio	20.372	16	0.204
Linear-by-Linear Association	0.981	1	0.322
N of Valid Cases	112		

H0: There is no significant association between the sector and experience.
H1: There is significant association between the sector and experience.
The Chi-square analysis reveals no statistically significant link between the two categorical variables, as the Pearson Chi-Square value ($\chi^2 = 19.728$, df = 16) has a significance level of p = 0.233, above 0.05. Likewise, the Likelihood Ratio test (p = 0.204) and the Linear-by-Linear Association test (p = 0.322) are also non-significant. As all p-values surpass the 0.05 level, the null hypothesis of no connection is accepted, indicating that the variables are independent in this sample of 112 genuine instances.

ANOVA – SECTOR AND VARIABLES

ANOVA		Sum of Squares	df	Mean Square	F	Sig.
HRA	Between Groups	4.679	4	1.17	5.418	0.001
	Within Groups	23.101	107	0.216		
	Total	27.78	111			
ORE	Between Groups	5.827	4	1.457	7.278	0
	Within Groups	21.414	107	0.2		
	Total	27.241	111			
ORS	Between Groups	6.016	4	1.504	5.631	0
	Within Groups	28.577	107	0.267		
	Total	34.593	111			

HO: There is no significant difference in HRA across the groups.
H1: There is a significant difference in HRA across the groups.
The ANOVA findings for HRA reveal a between-group sum of squares of 4.679 and a within-group sum of squares of 23.101. The computed F-value is 5.418, with a significance threshold of 0.001, which is below 0.05. Consequently, the null hypothesis (H_{01}) is dismissed. This outcome indicates that statistically significant disparities exist in HRA among the groups. The disparity between groups far exceeds the disparity within groups, suggesting that group affiliation affects HRA levels.
HO: There is no significant difference in ORE across the groups.
H2: There is a significant difference in ORE across the groups.
The ANOVA table for ORE indicates a between-group sum of squares of 5.827 and a within-group sum of squares of 21.414. The F-value is 7.278, and the significance level is 0.000 ($p < 0.05$). The null hypothesis (H_{02}) is rejected due to the p-value being below 0.05. This signifies that substantial disparities exist among the groups concerning ORE. The comparatively elevated F-value indicates that ORE exhibits significant group-based variance.
HO: There is no significant difference in ORS across the groups.
H3: There is a significant difference in ORS across the groups.
The ANOVA findings for ORS indicate a between-group sum of squares of 6.016 and a within-group sum of squares of 28.577. The computed F-value is 5.631, with a significance level of 0.000 ($p < 0.05$). The significance value being below 0.05 leads to the rejection of the null hypothesis (H_{03}). This verifies that ORS varies markedly among the groups. The findings demonstrate that group categorisation exerts a statistically significant influence on ORS.

Reliability Analysis

Statement	FL	CRONBACH ALPHA
HRAA1	0.691	0.921
HRAA2	0.704	

HRAA3	0.838	
HRAA4	0.711	
HRAA5	0.670	
HRAA6	0.537	
HRAA7	0.622	
HRAA8	0.647	
HRAA9	0.549	
HRAA10	0.823	
ORE1	0.806	
ORE2	0.684	
ORE3	0.764	
ORE4	0.722	
ORE5	0.748	
ORE6	0.734	
ORE7	0.742	
ORE8	0.754	0.926
ORS1	0.785	
ORS2	0.659	
ORS3	0.759	
ORS4	0.748	0.853

A high level of internal consistency was revealed by the measurement model, and it also exhibited adequate convergent validity across constructs. In terms of reliability, the Cronbach's alpha values for HR Analytics Adoption (α = 0.921), Organisational Efficiency (α = 0.926), and Organisational Support (α = 0.853) were found to be high, suggesting that these variables are very reliable. All of the factor loadings were higher than the minimum acceptable criterion of 0.50, with HR Analytics factor loadings ranging from 0.537 to 0.838, Organisational Efficiency factor loadings ranging from 0.684 to 0.806, and Organisational Support factor loadings ranging from 0.659 to 0.785. The values of the Average Variance Extracted (AVE) were excellent for Organisational Efficiency (about 0.55) and Organisational Support (approximately 0.54), which affirms the existence of convergent validity. On the other hand, HR Analytics demonstrated a somewhat lower AVE (approximately 0.46) despite its good reliability, which supports the overall construct adequacy. In general, the findings suggest that the measuring scales are reliable and have sufficient validity for the subsequent analysis of regression and moderation.

CLUSTER ANALYSIS:

Final Cluster Centers			
	1	2	3
Zscore(hra)	0.64378	-2.08428	-0.52551
Zscore(ore)	0.71095	-1.85147	-0.71792
Zscore(ors)	0.67143	-1.96540	-0.61176

There is a distinct distinction between the three groups, as demonstrated by the final cluster centres. Cluster 1 consists of respondents that have consistently above-average scores across all factors, Cluster 2 is comprised of a minority segment that has very low scores, and Cluster 3 is comprised of a group that is positioned in a moderate manner. The pattern indicates that there is a structured segmentation that extends from high to low levels across all of the dimensions that were investigated, which demonstrates that the three-cluster solution is both resilient and interpretable.

Number of Cases in each Cluster

Cluster	1	65.000
	2	11.000
	3	36.000
Valid		112.000
Missing		0.000

A strongly distinguished three-cluster solution is indicated by the findings, with the majority of respondents being identified as belonging to Cluster 1, a moderate segment being represented by Cluster 3, and a very tiny but distinct minority being classified as belonging to Cluster 2. The use of the segmentation strategy is validated as a result of the distribution, which provides evidence for the existence of diverse responder profiles within the sample.

Final Cluster Centers					
	1	2	3	F	Sig.
HRAA1	4.84	5.00	4.18	26.960	0.000
HRAA2	4.84	5.00	3.95	49.560	0.000
HRAA3	4.78	1.00	4.08	40.535	0.000
HRAA4	4.85	5.00	4.00	36.317	0.000
HRAA5	4.84	5.00	3.97	35.284	0.000
HRAA6	4.85	5.00	3.84	32.904	0.000
HRAA7	4.84	4.00	3.82	60.213	0.000
HRAA8	4.78	5.00	4.18	18.871	0.000
HRAA9	4.86	5.00	4.05	31.682	0.000
HRAA10	4.89	1.00	4.11	68.190	0.000
ORE1	4.89	1.00	4.03	106.534	0.000
ORE2	4.81	2.00	4.00	53.006	0.000
ORE3	4.84	5.00	3.84	54.152	0.000
ORE4	4.85	5.00	4.11	36.465	0.000
ORE5	4.90	5.00	4.00	55.203	0.000
ORE6	4.81	5.00	3.95	59.392	0.000
ORE7	4.85	5.00	4.00	57.258	0.000
ORE8	4.88	5.00	4.00	53.119	0.000
ORS1	4.88	5.00	3.82	65.498	0.000
ORS2	4.85	5.00	3.84	40.558	0.000
ORS3	4.86	5.00	3.89	45.688	0.000
ORS4	4.84	5.00	4.00	53.363	0.000

The K-means cluster analysis findings indicate a statistically significant three-cluster solution derived from the observed variables HRAA1–HRAA10, ORE1–ORE8, and ORS1–ORS4. The final cluster centres reveal distinct mean differences among the three groups, and the ANOVA findings demonstrate that all factors substantially distinguish the clusters ($p < 0.001$). The F-values, spanning from 18.871 to 106.534, exhibit robust discriminative capability, affirming that each item significantly enhances the segmentation framework. This indicates that the clustering solution is statistically sound and conceptually significant(Banker et al., 2020).

Cluster 1 has uniformly elevated mean scores for all items, often between 4.78 and 4.90. The consistency of these elevated scores across the HRAA, ORE, and ORS dimensions signifies a very positive and internally coherent respondent cohort. Members of this cluster have elevated levels across all assessed dimensions, indicating a robust correlation with the fundamental determinants addressed in the study. The stability and consistency of answers in this cluster indicate a well-defined segment marked by high involvement, positive impressions, or strong behavioural orientation, contingent upon the conceptual meanings of the variables.

Cluster 2, conversely, has a radically different reaction pattern. Although some items have exceptionally high mean scores (often 5.00), certain variables reveal markedly low values, such as 1.00 or 2.00. This polarised structure indicates that respondents in this cluster possess robust yet selective viewpoints, strongly agreeing with some propositions while vehemently opposing with others. The significant F-values for variables like ORE1 ($F = 106.534$) and HRAA10 ($F = 68.190$) suggest that these factors are crucial in differentiating this

group. The erratic yet pronounced response pattern suggests that this cluster signifies a unique minority group with distinct perspectives or experiences.
Cluster 3 exhibits a somewhat good character, with mean scores typically between 3.82 and 4.18. Despite the favourable reactions, they constantly fall short of those recorded in Cluster 1. This indicates a collective that exhibits consensus or favourable disposition, although with less intensity and conviction. The consistent results across factors suggest a balanced and stable segment situated between the very positive Cluster 1 and the polarised Cluster 2. This cluster may signify respondents who exhibit moderate engagement or cautious favorability towards the dimensions investigated in the study.
The three-cluster solution demonstrates a structured segmentation pattern with a very positive group, a somewhat positive group, and a polarised minority group(Banker, 2021). The statistical significance of all variables validates that the segmentation is substantial and underpinned by empirical distinction. The results indicate the existence of diverse respondent profiles within the sample, hence enhancing the analytical significance of cluster analysis in recognising unique patterns within the data.

ANOVA						
	Cluster		Error		F	Sig.
	Mean Square	df	Mean Square	df		
Zscore(hra)	42.334	2	0.242	109	175.234	0.000
Zscore(ore)	44.558	2	0.201	109	221.936	0.000
Zscore(ors)	42.633	2	0.236	109	180.585	0.000

HO: There is no significant difference among the identified clusters with respect to HRA.
H1: There is a significant difference among the identified clusters with respect to HRA.
The ANOVA findings indicate that the F-value for Zscore (HRA) is 175.234, with a significance level of 0.000 ($p < 0.001$). The null hypothesis (H01) is rejected due to the p-value being less than 0.05. This signifies that the clusters exhibit substantial differences regarding HRA. The considerable F-value indicates that between-cluster variance markedly exceeds within-cluster variance, affirming that HRA is crucial in differentiating responder segments.
HO: There is no significant difference among the identified clusters with respect to ORE.
H2: There is a significant difference among the identified clusters with respect to ORE.
The ANOVA findings for Zscore (ORE) indicate an F-value of 221.936 and a significance level of 0.000 ($p < 0.001$). The significance value is below the 0.05 level, leading to the rejection of the null hypothesis (H02). This verifies that statistically significant disparities are present among clusters regarding ORE. The greatest F-value among the three variables signifies that ORE possesses the most robust discriminating capacity in differentiating the clusters.
HO: There is no significant difference among the identified clusters with respect to ORS.
H2: There is a significant difference among the identified clusters with respect to ORS.
The results of the analysis of variance (ANOVA) for the Zscore (ORS) indicate that the F-value is 180.585, and the significance level is 0.000 ($p < 0.001$). It may be concluded that the null hypothesis (H0) is not true because the p-value is lower than 0.05. The fact that the clusters are so different from one another in terms of ORS is demonstrated by this. A high F-statistic implies that there is a significant amount of diversity between clusters, which lends evidence to the significance of ORS in determining cluster membership.
It has been established through the testing of the hypothesis that all three variables—HRA, ORE, and ORS—significantly distinguish the clusters respectively. In addition to demonstrating that each construct makes a significant contribution to segmentation, the fact that all null hypotheses were rejected suggests that the three-cluster solution is legitimate. ORE is the variable that has the most discriminating strength among the variables, followed by ORS and HRA, as seen by the F-values that are associated with each of these variables.

Findings and discussion

This study examined HR analytics adoption, organizational support, and organizational efficiency in Gujarati service sector firms to develop organizational profiles. Cluster analysis showed a three-cluster segmentation, demonstrating that analytics maturity and performance outcomes vary widely among firms. These data support the idea that HR analytics adoption varies by organization's technology preparedness, organizational support, and strategic integration.
Cluster 1 is the most advanced, scoring high on HR analytics adoption, organizational efficiency, and organizational support. Participants in this cluster strongly agreed with data-driven decision-making, strategic analytics utilization, and enhanced workforce results. This shows that firms in this cluster have better HR analytics maturity, integrating analytics into operational and strategic HR activities. According to Marler and Boudreau (2017), HR analytics helps firms integrate workforce initiatives with company goals and enhance decision-making. In contrast, Cluster 3 is fairly developed, with mean scores across all dimensions between

moderate and positive. This cluster's organizations may have partially institutionalized HR analytics but not analytics-driven decision-making. These companies likely use analytics for descriptive or operational objectives rather than predictive or strategic ones. This validates previous findings showing many organisations stay in the intermediate phases of HR analytics maturity due to analytical capabilities, technology infrastructure, or leadership commitment (Levenson, 2018).
Cluster 2, a tiny but separate portion with highly polarized reactions, is particularly intriguing. This cluster highly supported specific HR analytics practises but scored poorly on key organisational efficiency factors(Choksi et al., 2020). This shows that some organisations may have analytics capabilities but lack the organisational support or strategy alignment to turn analytics insights into performance outcomes. Such findings support Angrave et al. (2016), who argue that HR analytics tools alone do not improve organizational performance without appropriate managerial practices and organizational culture. The ANOVA findings demonstrate that the research factors distinguish the clusters. HR analytics adoption, efficiency, and support have substantial F-values ($p < 0.001$), highlighting their significance in identifying organizational profiles. Organizational efficiency had the highest discriminating power, demonstrating that analytics maturity is measured by worker productivity, engagement, and operational performance. This supports the idea that HR analytics improves workforce management and evidence-based decision-making (Rasmussen & Ulrich, 2015). Organizational support for HR analytics deployment is another key finding from the study. A data-driven culture, competent leadership, and suitable technology infrastructure were indicators of advanced analytics cluster membership. Previous study has shown that organisational preparation and leadership commitment are necessary for analytics deployment (Minbaeva, 2018). Analytics efforts may stay underused and fail to deliver corporate advantages without proper support. The demographic research also showed that over 70% of respondents had less than five years of professional experience. This may affect views of HR analytics uptake and performance in firms when younger workers enter analytics-related fields. Future research may benefit from involving more senior HR managers and decision-makers to better understand strategic analytics adoption.
This study shows that firms may be categorized by analytics adoption and supportive organizational factors, adding to HR analytics literature. The results imply that HR analytics performance gains are greater for organisations with strong institutional backing and a commitment to data-driven decision-making. Additionally, a polarized cluster emphasizes the difficulty faced by firms that implement analytics tools without having the organizational capacity to use them successfully. These findings emphasise the necessity of understanding HR analytics as a strategic organisational skill that requires alignment across analytics infrastructure, leadership support, and workforce management practises.

Managerial Implications

This study has numerous major implications for managers, HR practitioners, and organizational leaders using HR analytics to improve workforce management and efficiency. The results emphasize the need to include HR analytics into strategic HR decision-making. Advanced analytics cluster organizations have continuously greater efficiency and performance. This recommends that firms should engage in predictive workforce planning, talent analytics, and performance forecasts instead of descriptive reporting. Analytics-driven HR strategies help companies make better hiring, training, retention, and engagement decisions.
Second, the report stresses the need of organizational support for HR analytics deployment. Advanced analytics firms have higher leadership support, technology infrastructure, and a data-driven decision-making culture, according to cluster analysis. This means HR analytics efforts need top management backing to thrive. Therefore, organizations should invest in HR information systems, analytics tools, and staff training programs that improve HR department analytics. Third, the findings show HR workers should be trained in analytics. HR personnel may lack the analytical abilities to evaluate worker data, thus many firms are still adopting analytics. HR analytics training, professional development, and data analyst cooperation may help firms mature their analytics.
Fourth, a polarized cluster in the research suggests that analytics tools alone cannot improve performance. Some firms have analytics infrastructure but fail to apply analytics to management. This shows the necessity of connecting analytics projects with organizational strategy and incorporating analytics insights into daily decision-making.
Finally, segmenting firms into analytics maturity profiles helps managers analyze their HR analytics progress. Organizations may assess their analytics skills and build tailored strategies for advanced, intermediate, or developing categories. Organizations may enhance worker outcomes and analytics maturity by gradually enhancing organizational support structures and integrating analytics across HR departments.

Conclusion and Future Research Directions

This study studied HR analytics implementation in Gujarati service sector firms by developing organizational characteristics based on HR analytics adoption, support, and efficiency. The study identified three categories of firms with differing analytics maturity and performance results using cluster analysis. Strong analytics adoption and organizational support lead to greater organizational efficiency, including worker productivity, engagement, and operational performance. Lower efficiency results are seen in firms with insufficient analytics

integration or institutional support. These findings emphasize the need to combine technical analytics with supporting organizational structures to maximize HR analytics advantages.
The study adds to HR analytics literature by showing how firms may be categorized by analytics maturity. This study uses segmentation to identify service sector organizational characteristics rather than concentrating on causal correlations between HR analytics and performance. This approach provides a deeper understanding of HR analytics practices across firms and how institutional support affects analytics projects. Despite its contributions, the study has some limitations that should be noted when interpreting the results. The study began by examining Gujarati service sector firms. Therefore, the findings may not be generalizable. Future research might expand the study to additional locations, sectors, or countries to further understand HR analytics use.
Finally, digital transformation projects, organizational learning capacities, and leadership styles may affect HR analytics maturity in future study. Advanced analytical methods like structural equation modeling or multi-group analysis may assist researchers grasp the intricate links between HR analytics, organizational support, and performance results. This study shows that HR analytics is becoming a key skill that improves workforce management and organizational efficiency. Strong analytics skills and supportive organizational cultures will be important for preserving competitive advantage as firms increasingly use data-driven decision-making.

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