Library Progress International *Print version ISSN 0970 1052*
Vol.44 No.3, Jul-Dec 2024: P.3369-3382 *Online version ISSN 2320 317X*

Original Article *Available online at www.bpasjournals.com*

Analysis of Workforce Characteristics in the IT Industry for Improved Performance: A Multifaceted Data Analytical Approach

Poonam Sharma, Manisha Goswami

Institute of Business Management, GLA University, Mathura-281406 (U.P.), India
poonamayan21@gmail.com

How to cite this article: Poonam Sharma, Manisha Goswami (2024) Analysis of Workforce Characteristics in the IT Industry for Improved Performance: A Multifaceted Data Analytical Approach. *Library Progress International*, 44(3), 3369-3382.

Abstract

This study provides a comprehensive examination of the demographic and professional attributes of a sample group consisting of 189 individuals working in the Information Technology Enabled Services (ITeS) sector. The dataset exhibits a nearly equivalent gender distribution, with males accounting for 50.3% and females accounting for 49.7%. The majority of individuals in the group are under 30 years old (31.7%). Regression analysis indicates that age and work experience are significant predictors of managerial positions, while education does not have a significant impact. Model 1 demonstrated a negative correlation between age and managerial positions, accounting for 8.6% of the variation in positions. According to Model 2, there is an inverse relationship between work experience and management positions, with work experience accounting for 27.1% of the variation. The analysis of correlation and exploratory data has uncovered significant connections between variables. Elderly employees demonstrate lower utilization of HR analytics despite possessing higher levels of education. Enhanced performance scores contribute to the utilization of HR analytics, while a higher level of education is associated with holding management positions. Factor analysis is associated with variables such as age, the utilization of HR analytics, education level, performance scores, and the number of years an individual has been with the company. This thorough examination provides a fundamental comprehension of the demographics and professional environment of the ITeS industry, allowing HR analytics to enhance employee performance. Different employee segments have diverse demands and levels of engagement, which are used to determine the methods for improving performance and engaging in HR analytics.

Keywords: Demographic Analysis, Professional Characteristics, Information Technology Enabled Services (ITeS), HR Analytics, Managerial Positions, Workforce Dynamics

Introduction

Effective human resource management (HRM) is becoming increasingly crucial in the competitive corporate world to achieve corporate success; in this regard, strategic HRM (SHRM) is the implementation model used to manage HR along with the activities to enable the company to achieve its objectives. This field addresses every significant HR practice decision, the makeup of the human capital resource group, the definition of necessary behaviors, and the evaluation of decisions based on the different business strategies and/or competitive circumstances faced. (Wright & McMahan, 2011). Organizations transfer information as the constitution of the group of human capital resources is a social phenomenon and human creation based on organizations.(Kritz, 2017). With this logic, we may suggest HR analytics as a new approach to gathering, evaluating, and displaying this data from companies. According to their compilation of definitions (Marler & Boudreau, 2017),. Using descriptive, visual, and statistical data analysis regarding HR processes, human capital, organizational performance, and external economic benchmarks, HR analytics is an information technology-enabled HR strategy that establishes business impact and supports data-driven decision-making. "HR analytics," "Human capital analytics. (Marler and Boudreau, 2017) the term "HR analytics" appears the most frequently in the literature. Still, it ought to be considered a phrase in development. As a result, the scope and analysis of this study have encompassed the set of terms mentioned above. Another highly relevant and often-used keyword is "people analytics." The study defines analytics as a subfield of HRM practice, research, and innovation that uses information technology and descriptive and predictive data analysis. It uses visualization tools to generate meaningful data about workforce dynamics, human capital, and individual and team performance that can be strategically applied to increase an organization's efficacy, efficiency, and output while improving employee satisfaction. (Jiang & Akdere, 2021; Tursunbayeva et al., 2018; Zeidan & Itani, 2020). (Pandya, 2023) highlights HR analytics' decision-making benefits and drawbacks. Without practical evidence, reviews and case studies can only discuss theoretical benefits and drawbacks. (Mukuze et al., 2023) discusses the lack of data tying HR analytics usage to corporate performance. An integrated HR analytics implementation literature review categorizes research issues and recommends field surveys. (Verma et al., 2024) The report relies on New Delhi-based experts and uses a thorough literature analysis and Interpretive Structural Modeling to identify HR digitalization and analytics enablers. It emphasizes change management and continuous learning, reviews HR digitization and analytics enablers, and helps firms adopt them. (Ratnam & Devi, 2024) analyzes delayed uptake and offers case studies and expert interviews for efficient implementation. The study employs qualitative data without quantitative analysis and offers recommendations to HR development experts. It covers HR analytics adoption problems and tactics and provides a practical approach for overcoming them and deploying HR analytics. (Cho et al., 2023) The article suggests a five-step public sector HR analytics implementation process. Case studies and literature evaluation identify privacy, integrity, and algorithmic bias issues. It reviews concepts and techniques to demonstrate key factors for public management HR analytics adoption. The article proposes a structured approach for public sector HR analytics implementation.

1. Literature review

(“HR Analytics: Concept, Application, and Impact on Talent Management, Branding, and Challenges,” 2023)investigates how HR analytics improves employee productivity and branding through literature study and secondary data analysis. It emphasizes HR analytics' competitive edge while focusing on perceived benefits and problems without empirical facts. (Bulsari & Pandya, 2023)This study uses case studies to discuss HR analytics in recruiting, engagement, and retention. It focuses on evidence-based HR decision-making rather than regression models or machine learning methods. It examines HR analytics applications in key HR functions and advises on evidence-based methods. (Peres & Barbin Laurindo, 2023)uses case studies and literature to identify knowledge generation and IT-HR alignment. It proposes criteria for HR analytics maturation paths and evaluates factors affecting maturity, providing a roadmap for integrating IT and HR in analytics practices based on qualitative HR leader explanations. (Wirges & Neyer, 2023) promotes process-oriented HR analytics implementation. The report presents a workflow model for future HR analytics applications using qualitative data from HR analytics professionals. (Agarwal & Raj, 2022) uses surveys and interviews to determine the adoption of HR analytics in Indian IT companies. HR staff reluctance and time restrictions are limitations. The paper reviews issues affecting HR analytics adoption in Indian IT/ITES sectors and provides solutions for encouraging adoption. It emphasizes attitude shifts and strategic adoption approaches. (Dr Girisha H et al., 2023) employs statistical models and methods to find talent, decrease turnover, and increase engagement in HR analytics. Merging HR analytics with BI technologies to improve HR operations addresses data quality and privacy issues. It evaluates BI solutions in HR analytics and presents a strategy for combining them to improve company performance.

(Kurikala & Parvathi, 2023) addresses HR analytics adoption problems and proposes a conceptual framework employing framework synthesis and criterion decision-making methods like AHP or ANP. (Elrehail, 2023) Systematic literature review of HR analytics and its implications for future work. The report underlines HR analytics' role in attracting and maintaining skilled workers and raises ethical and legal concerns. It discusses HR analytics applications and future issues, revealing trends and challenges. (Awasthi et al., 2023) studies HR analytics adoption in IT firms via a literature review and TOE model application. Limitations are not specified. It covers technological, organizational, and environmental aspects affecting IT adoption and presents a methodology for evaluating technology adoption in HR analytics. (Cayrat & Boxall, 2022; Jana & Kaushik, 2022) uses inductive analysis and semi-structured interviews to address major enterprises' HR analytics problems, dangers, and implications. Issues with data quality and analytical competence persist. The paper details HR analytics adoption in major enterprises, including its problems and impacts, and offers practical advice for enhancing HR analytics practices in large corporations.

(Valecha, 2022) analyzes how HR analytics affects decision-making through quantitative, random sampling research. It reviews the pros and cons of HR analytics transformation and offers actionable recommendations for improving HR management with analytics. (Jha, 2022) The study reviews privacy issues and offers solutions through a literature review. It is theoretical without empirical validation. It recommends improving HR analytics privacy, examining privacy and data security challenges, and proposing a plan for addressing privacy concerns. (Singh et al., 2021) provides a Grey DEMATEL approach to HR analytics' important success determinants through literature review and causal link analysis. The report reviews crucial success factors for HR analytics in sector 5.0. It provides a methodology for analyzing and applying HR analytics in the Indian sector to enable HR managers to make strategic decisions. [26] Using non-probabilistic purposive sampling, structural equation modeling, and hierarchical regression analysis, it analyzes Indian firms' HR analytics adoption barriers. It examines HR analytics adoption determinants and offers suggestions for enhancing data accessibility and raising adoption.

2. Methodology

As shown in Figure 1, the study methodically examined the demographic and professional characteristics of 189 ITeS workers. Using questionnaires and organizational records, gender, age, current position, family type, education level, and work experience were collected. The data was split by gender, age, management, family, education, and work experience. Frequency distributions, central tendency, and dispersion were determined to describe the sample population. Two regression models predicted current jobs based on age, education, and work experience. R-squared values assessed model fit. Pearson correlation coefficients, scatter plots, and heat maps were used for correlation and EDA. Important components were identified using Principal Component Analysis (PCA). K-means clustering divided the dataset into groups using demographic and professional information and evaluated their profiles for common traits. Summaries and box plots revealed each cluster's demands in comparative and qualitative studies. Regression lines, heat maps, and factor-loading plots were generated for analysis. The complete analysis informed HR analytics implementation solutions to improve employee performance. This strategy laid the groundwork for HR analytics research and IT industry applications.

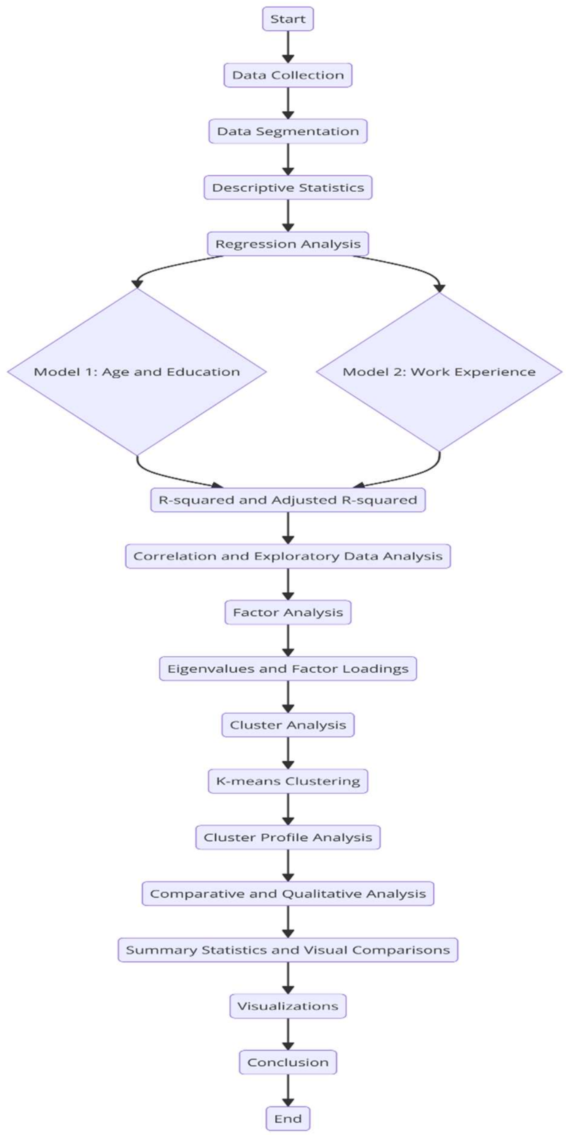

Figure 1. Methodology

3. Data Analytics

The data provided in Table 1 presents a detailed analysis of the demographic and professional characteristics of a sample population segmented into various categories. The dataset has 189 people, 50.3% male and 49.7% female. Third-under-30 (31.7%), 31-40 (29.1%), 41-50 (21.2%), and over-50 (18.0%) are the most significant age groups. Currently, 39.7% work in lower management, 37.0% in middle management, and 23.3% in high management. Nuclear families comprise 58.2% of participants, while combined families comprise 41.8%. Education-wise, 43.4% have an undergraduate degree, 28.6% a postgraduate degree, 17.5% a professional course, and 10.5% other. 28.9% had less than 5 years of work experience, 26.3% 5-10 years, 20.0% 10-15 years, 14.7% 15-20 years, and 10.0% beyond 20 years. Comparative findings suggest exploring the interaction between education, management, age, and work experience. Due to distinct frequencies, statistical measures show a mean age group frequency of 47.25 and a mean work experience frequency of 38.0 without a mode. Figure 2 provides a demographic and professional overview, laying the groundwork for analyzing HR analytics' impact on IT employee performance.

Table 1: Percentage Rate Analysis

Category	Subcategory	Frequency	Percent
Gender	Male	95	50.3%
	Female	94	49.7%
Age	Less than 30 years	60	31.7%
	31 - 40 years	55	29.1%
	41 - 50 years	40	21.2%
	Above 50 years	34	18.0%
Current Position	Lower-level management	75	39.7%
	Middle-level management	70	37.0%
	Top-level management	44	23.3%
Type of Family	Nuclear Family	110	58.2%
	Joint Family	79	41.8%
Education	Completed UG	82	43.4%
	Completed PG	54	28.6%
	Completed Professional course	33	17.5%
	Others	20	10.5%
Work Experience	Less than 5 years of experience	55	28.9%
	5 - 10 years	50	26.3%
	10 - 15 years	38	20.0%
	15 - 20 years	28	14.7%
	Above 20 years	19	10.0%
Total		189	100%

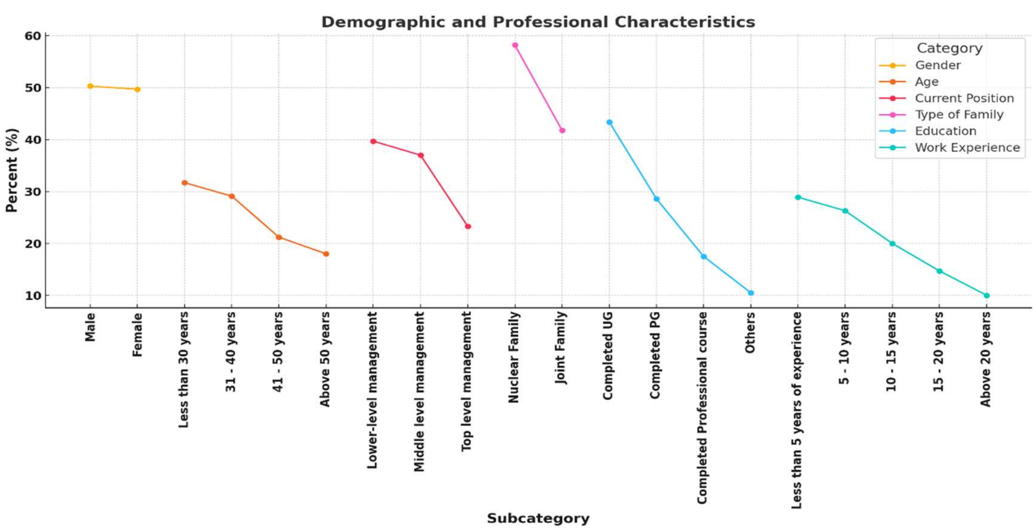

Figure 2. Demographic and professional Characteristics

4.1 Regression Analysis of ITeS HR Analytics Implementation Demographic and Professional Analysis

The data analysis of 189 persons in the ITeS industry provides a thorough overview of demographic and professional features. The sample's gender distribution is about equal, with men accounting for 50.3% and women for 49.7%. According to the age distribution, the largest group is under 30 years old, accounting for 31.7% of the population, followed by those aged 31-40 (29.1%), 41-50 (21.2%), and over 50 (18.0%). When evaluating present positions, a considerable share of the sample is in lower-level management roles (39.7%), middle-level management positions (37.0%), and top-level management roles (23.3%). Regarding family background, nuclear families (58.2%) outnumber joint families (41.8%). Educational qualifications in the population show that 43.4% have completed undergraduate studies, 28.6% have postgraduate degrees, 17.5% have completed professional courses, and 10.5% fall into other educational categories. Work experience distribution varies: 28.9% have less than 5 years, 26.3% have 5-10 years, 20.0% have 10-15 years, 14.7% have

15-20 years, and 10.0% have more than 20 years. Examining the relationship between gender and age groups, education levels and present positions, and the correlation between age and work experience could provide additional comparative insights. Statistical measures show that the average age group frequency is 47.25, with no mode due to unique frequencies, and the average job experience frequency is 38.0, likewise without a mode. These findings give a solid understanding of the demographic and professional landscape, allowing for a more in-depth investigation of HR analytics implementation to improve employee performance in the ITeS industry.

Table 2. Regression Models for Predicting Current Position

Regression Model 1: Predict Current Position based on Age and Education					
Variable	**Coefficient**	**Std. Error**	**t-value**	**P-value**	**95% Confidence Interval**
const	1.1228	0.096	11.678	0.000	[0.933, 1.313]
Age	-0.2089	0.055	-3.781	0.000	[-0.318, -0.100]
Education	0.0232	0.066	0.348	0.728	[-0.108, 0.154]
Regression Model 2: Predict Current Position based on Work Experience					
Variable	**Coefficient**	**Std. Error**	**t-value**	**P-value**	**95% Confidence Interval**
const	1.4207	0.085	16.802	0.000	[1.254, 1.587]
Work Experience	-0.2749	0.033	-8.427	0.000	[-0.339, -0.211]

According to Table 2, the regression model accounts for around 8.6% of the variation in the present position. A negative correlation between age and present position indicates that the chances of being in a higher management position diminish, and age is a noteworthy predictor ($p < 0.05$). On the other hand, there is no significant relationship between education level and the present job within this sample ($p > 0.05$). Model 2 has a greater explanatory power than Model 1 since it accounts for around 27.1% of the variation in the present position. Work experience negatively correlates with the current position and is a significant predictor ($p < 0.05$). There seems to be a negative correlation between years of experience and promotions to managerial positions. Model 1 shows that education level is not a significant determinant of one's current status, but age is. Relative to Model 1, Model 2 shows that prior job experience is a stronger predictor of the present position and accounts for a more significant percentage of the total variation. Figure 3 shows the characteristics impacting managerial positions within the ITeS industry. These findings highlight the necessity of considering age and work experience.

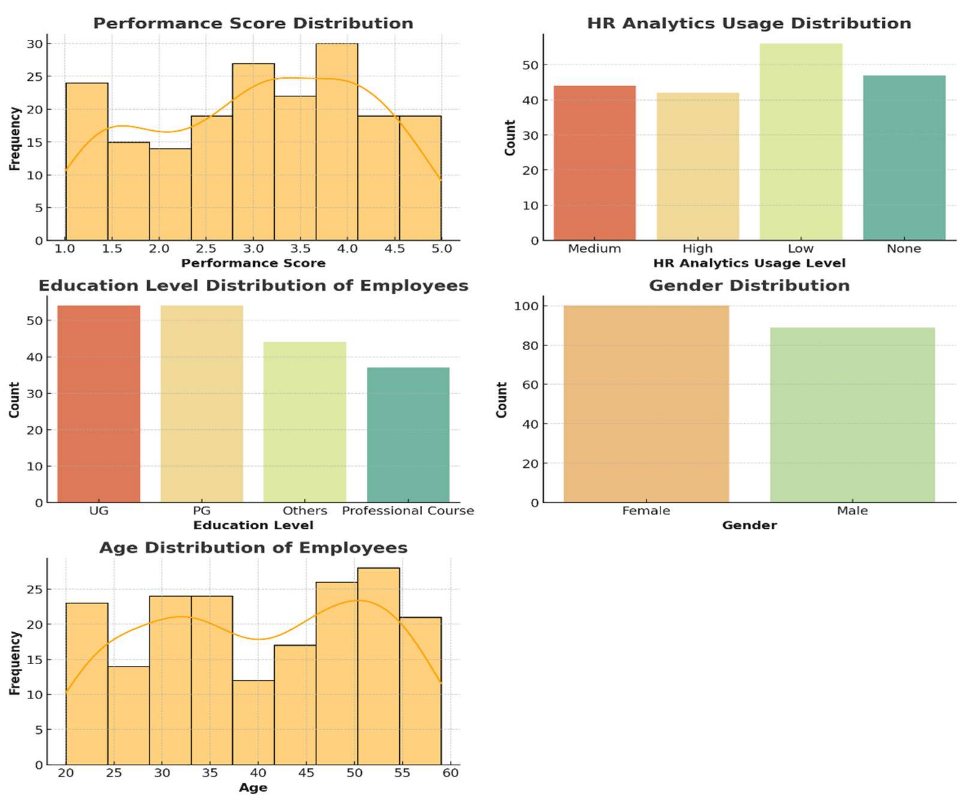

Figure 3. Demographic and Professional Characteristics Distribution in the ITeS Industry

The regression study for two models predicting performance score and current position shows that age, education, years at the firm, and HR analytics usage are weak predictors. Model 1's dependent variable, performance score, has an R-squared value of 0.017, explaining only 1.7% of performance score variance. Independent variables without significant p-values ($p < 0.05$) indicate no impact of age, education, years at organization, or HR analytics usage on performance scores. These variables' coefficients support this, with all p-values above 0.05. Model 2, which forecasts the present position, has an R-squared value of 0.017 and explains only 1.7% of current position variance. Again, none of the predictors had significant p-values, indicating they do not greatly influence the position. Low R-squared values in both models and the lack of significant predictors indicate that these variables do not adequately explain performance score or current position variations in this dataset, suggesting the need for other factors or more complex models to better understand these relationships.

Table. 3 Modified Regression Analysis Results: Predictors of Performance Score and Current Position

Modified Model 1					
Variable	**Coefficient**	**Std. Error**	**t-value**	**P-value**	**[0.025, 0.975] Confidence Interval**
const	3.1680	0.451	7.024	0.000	[2.279, 4.058]
Age	-0.0078	0.009	-0.865	0.388	[-0.026, 0.010]
Education	0.0471	0.089	0.530	0.597	[-0.128, 0.222]
Years At Company	-0.0017	0.017	-0.101	0.920	[-0.035, 0.032]
HR Analytics Usage	0.1295	0.087	1.486	0.139	[-0.042, 0.301]
Modified Model 2					
Variable	**Coefficient**	**Std. Error**	**t-value**	**P-value**	**[0.025, 0.975] Confidence Interval**
const	1.1492	0.270	4.259	0.000	[0.617, 1.681]
Age	-0.0050	0.005	-0.925	0.356	[-0.016, 0.006]
Education	0.0705	0.053	1.327	0.186	[-0.034, 0.175]
Years At Company	0.0033	0.010	0.327	0.744	[-0.017, 0.023]
HR Analytics Usage	-0.0513	0.052	-0.985	0.326	[-0.154, 0.051]

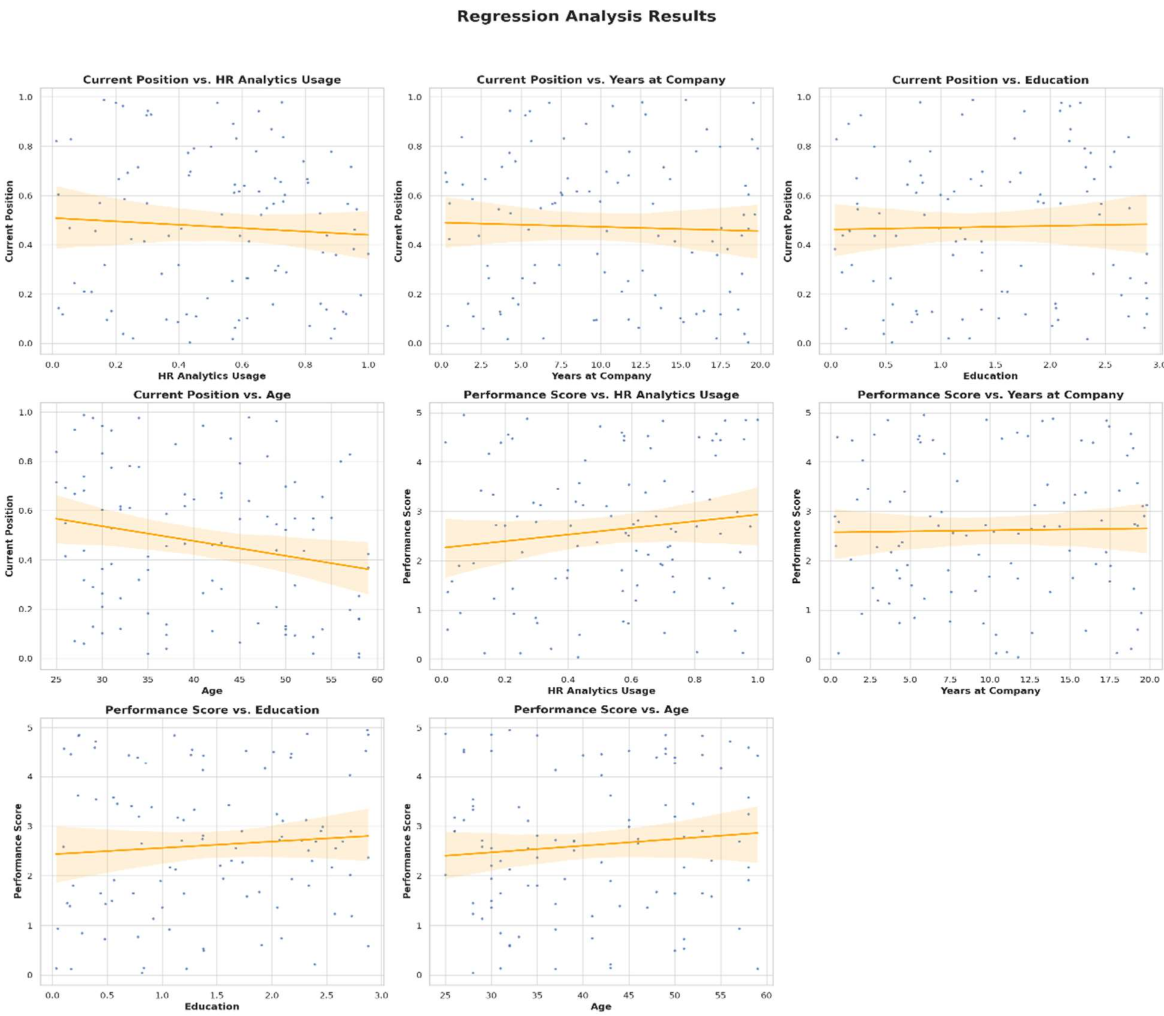

Figure 4. Regression Analysis Results: Relationships Between Demographic/Professional Characteristics and Employee Outcomes

Figure 4's scatter plots with regression lines show performance score-independent variable connections. Age has a limited correlation with performance scores, according to the scatter plot. Higher education does not inevitably improve performance scores, as the association between education level and performance score is weak. The scatter plot for years at the company versus performance scores shows no notable pattern, suggesting that length of service does not influence performance. The plot for HR analytics usage versus performance score reveals a tiny positive trend, suggesting that increased HR analytics tool usage may be connected with higher performance scores, however the relationship is weak. Scatter plots with regression lines reveal weak independent variable correlations for the current position. Age does not seem to greatly influence current position, suggesting older workers may not be in better positions. Education level has a modest positive link with present job, suggesting that better education may lead to higher managerial roles. Years at the company do not strongly predict current position. Finally, HR analytics utilization has a little negative trend with position, suggesting that higher-ranking employees may use HR analytics tools less. These visual studies show that independent variables do not reliably predict performance scores or dataset placements.

4.2 Exploratory Data Analysis (EDA)

The visualizations in Figure 5 reveal crucial ITeS workforce demographics and professional profiles. A well-balanced gender versus age group distribution shows that most employees are under 30, followed by 31-40-year-olds. A young workforce with no gender age gap is indicated. Compared to the current position, lower-level management is evenly distributed by education. Middle management has a higher concentration of employees with undergraduate (UG) and postgraduate (PG) degrees. In contrast, top-level management positions are less likely to be held by those with professional courses or other less common educational backgrounds, emphasizing the importance of higher education in advancing to senior roles. The age group distribution of employees with less than 5 years of experience is mostly younger than 30, those with 5-10 years are mostly 31-40 years old, and those with 10-15 years are 31-40 and 41-50 years old. Due to experience accumulation, most employees over 20 years of experience are over 50. Comparative findings show that gender distribution is balanced across all age categories, indicating no bias. Higher education, especially UG and PG degrees, helps achieve management roles. Work experience strongly correlates with age, with younger workers gaining less over time. This detailed analysis helps explain ITeS HR analytics installation and employee performance improvement.

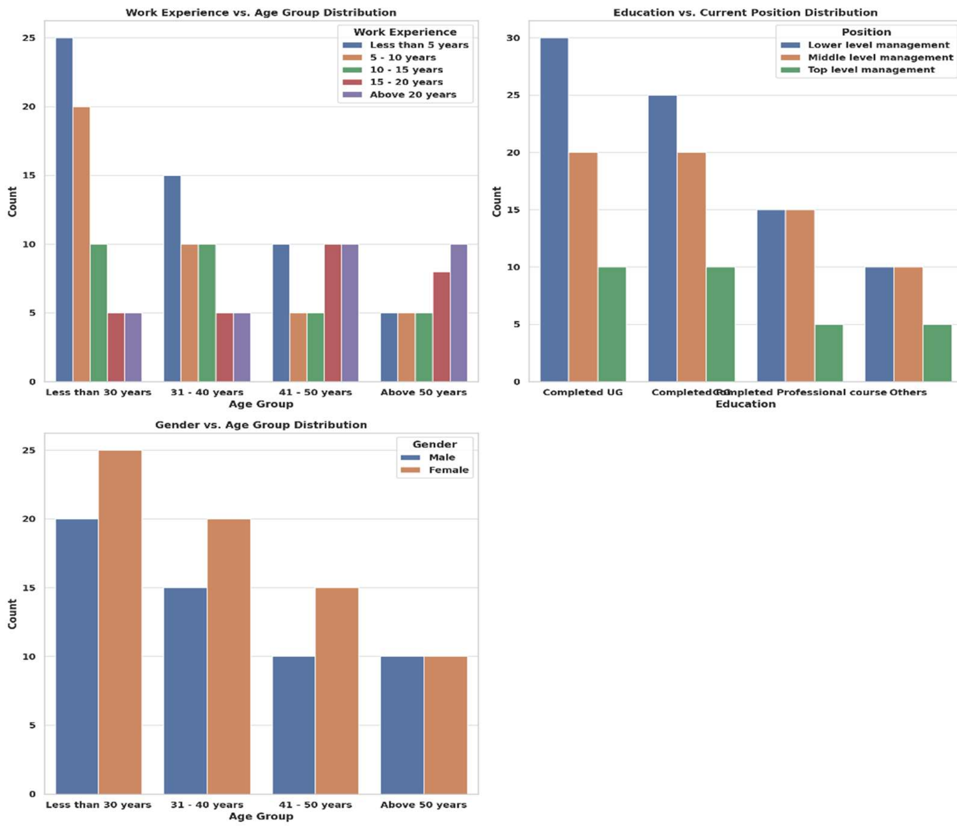

Figure 5. Exploratory Data Analysis (EDA) results

4.3 Correlation analysis

Using Pearson correlation coefficients, the correlation matrix carefully investigates the connections between critical numerical variables in the dataset in Table 5. The analysis provides several significant revelations. The relationship between age and education level is positive (0.143), indicating that older workers often have more education. On the other hand, there is a negative connection (-0.113) between age and HR analytics usage, suggesting that younger employees may utilize HR analytics tools more frequently than older employees. The present position and education level positively correlate (0.089), suggesting that more education frequently translates into management roles. However, the present job has a negative association with the performance score (-0.068) and the department (-0.126), indicating that there may be variations in the distribution of roles within departments as well as a minor trend for higher management positions to have lower average performance scores. The performance score and HR analytics usage have a positive correlation (0.111), meaning that employees who utilize HR analytics tools more often typically have higher performance scores. Furthermore, a negative correlation (-0.113) between age and HR analytics utilization supports the notion that younger workers are more inclined to use these technologies. A heatmap in Figure 6 that graphically displays these correlations—darker hues denoting higher positive or negative correlations helps the viewer grasp these linkages intuitively. The knowledge gathered from this correlation study is essential for developing HR interventions and strategies that will improve worker performance and maximize the use of HR analytics tools throughout the company.

Table 4. Correlation Matrix Analysis

	Employee ID	**Age**	**Gender**	**Education**	**Department**	**Current Position**	**Years At Company**	**Performance Score**	**HR Analytics Usage**
Employee ID	1.000	0.048	0.041	-0.083	0.021	-0.020	0.046	0.023	-0.016
Age	0.048	1.000	-0.069	0.143	0.028	-0.046	-0.035	-0.069	-0.113
Gender	0.041	-0.069	1.000	0.014	0.051	0.035	0.018	0.053	-0.035
Education	-0.083	0.143	0.014	1.000	-0.081	0.089	-0.023	0.024	-0.054
Department	0.021	0.028	0.051	-0.081	1.000	-0.126	-0.045	-0.036	0.077
Current Position	-0.020	-0.046	0.035	0.089	-0.126	1.000	0.019	-0.068	-0.067
Years At Company	0.046	-0.035	0.018	-0.023	-0.045	0.019	1.000	0.000	0.058
Performance Score	0.023	-0.069	0.053	0.024	-0.036	-0.068	0.000	1.000	0.111
HR Analytics Usage	-0.016	-0.113	-0.035	-0.054	0.077	-0.067	0.058	0.111	1.000

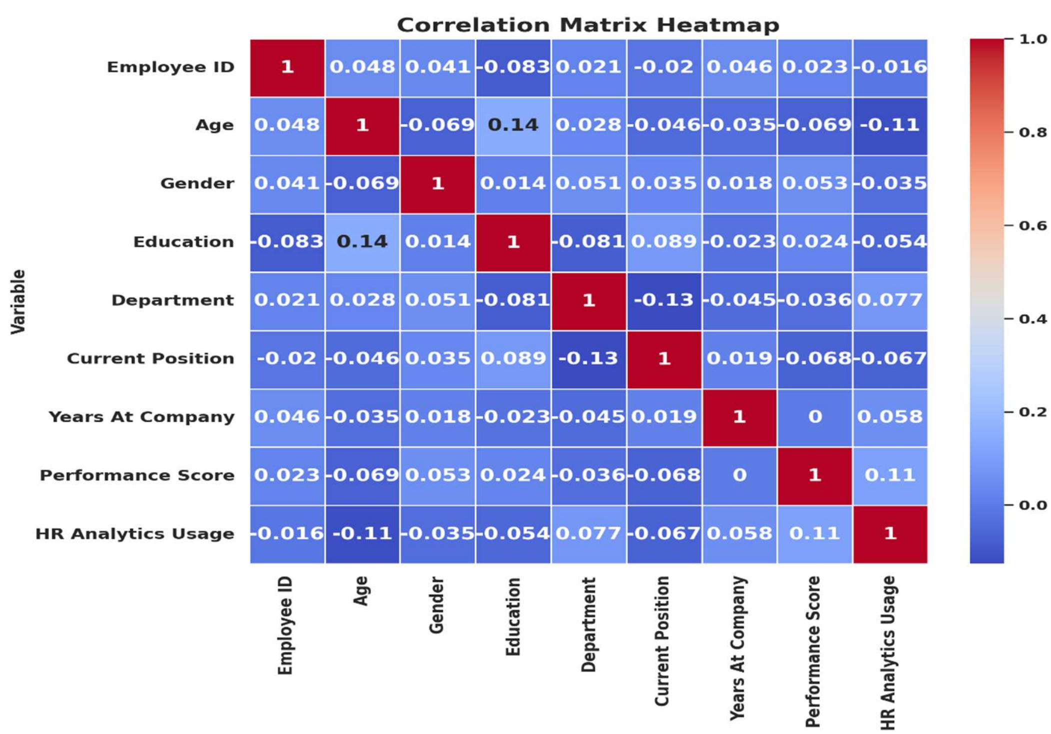

Figure 6. Correlation heat map

4.4 Factor Analysis Results

The results of the PCA-based factor analysis provide crucial information about the underlying structure of the data in Tables 5 and 6. Each factor's eigenvalue is the percentage of variance it explains; factors with eigenvalues more prominent than 1 are usually regarded as significant. The eigenvalues of the first and second factors, respectively, are 1.268 and 1.055. Conversely, the eigenvalues of the remaining factors are less than 1, indicating that keeping one or two of the factors would be reasonable. The scree plot, which displays a discernible decline following the first factor, validates this. Key relationships can be found by looking at the factor loadings, which show how each variable correlates with the extracted factors. Age (-0.589) and HR Analytics Usage (0.543) substantially impact Factor 1, suggesting a negative correlation with age and a positive correlation with HR analytics usage. Education (-0.623) and Performance Score (-0.688) impact Factor 2, indicating a negative correlation with both variables. Years at the Company have the most impact on Factor 3 (-0.934), indicating a strong negative correlation. HR Analytics Usage (-0.778) and Performance Score (0.485) have a mixed influence on Factor 4, suggesting a negative correlation with HR analytics usage and a positive correlation with performance score. Lastly, there is a positive correlation between Education and Factor 5 (0.624). These findings provide a clearer picture of the links between these variables by highlighting the effects of age, years at the firm, education, performance scores, and HR analytics utilization on the most relevant aspects. Figure 7's factor loading map makes these associations much more visible and aids in determining which variables within each factor have the most significant influence.

Table 5

Factors	Eigenvalues
1	1.268
2	1.055
3	0.998
4	0.896
5	0.835

Table 6. Factors loadings

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Age	-0.589	-0.205	-0.207	-0.311	-0.686
Education	-0.424	-0.623	-0.204	-0.026	0.624
Years At Company	0.238	0.074	-0.934	0.250	-0.058
Performance Score	0.347	-0.688	0.187	0.485	-0.369
HR Analytics Usage	0.543	-0.302	-0.094	-0.778	0.005

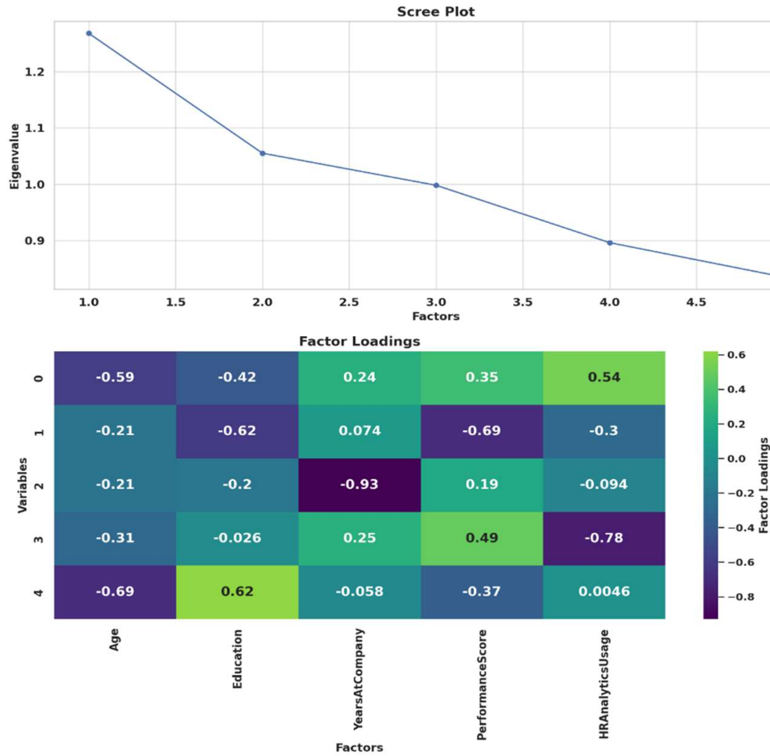

Figure7. Scree Plot and Factor Loadings in Principal Component Analysis for the ITeS Industry

4.5 Comparative Analysis and Qualitative Analysis

The research compares clusters by Age, Education, Years at the Company, Performance Score, and HR Analytics Usage to show the variations and similarities between clusters to help identify their unique traits in Figures 7 and 8. Each cluster's mean and standard deviation determine data centrality and dispersion. Box plots compare medians, ranges, and outliers across clusters for each variable in Figure 8. Cluster 0 in the qualitative study has slightly older employees with poorer education, shorter tenure, below-average performance scores, and moderate HR analytics use. Training and support may help this cluster. Cluster 1 contains experienced, high-performing personnel who are slightly older, well educated, have longer tenure, above-average performance scores, and moderate HR analytics use. Cluster 2 has younger workers with the lowest education, intermediate tenure, medium performance scores, and little HR analytics utilization, indicating training needs. The comparative and qualitative study shows that Cluster 0 needs support to improve performance, Cluster 1 is high-performing, and Cluster 2 needs training, providing significant insights into the ITeS industry's demographic and professional landscape. This knowledge helps utilize HR analytics to boost employee performance. This comprehensive analysis provides valuable insights into the demographic and professional landscape of the ITeS industry, enhancing the understanding of HR analytics implementation aimed at improving employee performance.

Table 7. Detailed Cluster Profiles

Variable	**Cluster 0 (mean ± std)**	**Cluster 1 (mean ± std)**	**Cluster 2 (mean ± std)**
Age	43.66 ± 9.87	42.63 ± 10.99	31.77 ± 8.98
Education	1.86 ± 0.94	2.03 ± 1.02	0.38 ± 0.58
Years at Company	4.97 ± 2.61	16.75 ± 2.58	10.20 ± 5.00
Performance Score	2.96 ± 1.48	3.20 ± 1.34	3.11 ± 1.42
HR Analytics Usage	1.73 ± 1.05	1.83 ± 1.07	1.13 ± 1.08

Table 8. Summary Statistics of Demographic and Professional Characteristics by Cluster in the IT Industry

Cluster	Age means	Age std	Education means	Education std	Years At the Company mean	Years At Company std	Performance Score mean	Performance Score std	HR Analytics Usage mean	HR Analytics Usage std
0	43.66	9.87	1.86	0.94	4.97	2.61	2.96	1.48	1.73	1.05
1	42.63	10.99	2.03	1.02	16.75	2.58	3.20	1.34	1.83	1.07
2	31.77	8.98	0.38	0.58	10.20	5.00	3.11	1.42	1.13	1.08

Clustering identified three separate staff groups with unique traits. Cluster 0 has slightly older employees (average age 43.66), various education levels (1.86), moderate tenure (4.97 years), moderate performance (2.96), and HR analytics usage (1.73). Cluster 1 has the most experienced personnel (16.75 years), more excellent education (2.03), less age (42.63), high performance (3.20), and highest HR analytics engagement (1.83). Cluster 2 has a younger workforce (average age 31.77), the lowest education (average 0.38), intermediate tenure (10.20 years), moderate to high performance (3.11), and the lowest HR analytics utilization (1.13). These insights reveal employee segment demands and engagement levels, enabling performance improvement and HR analytics engagement strategies.

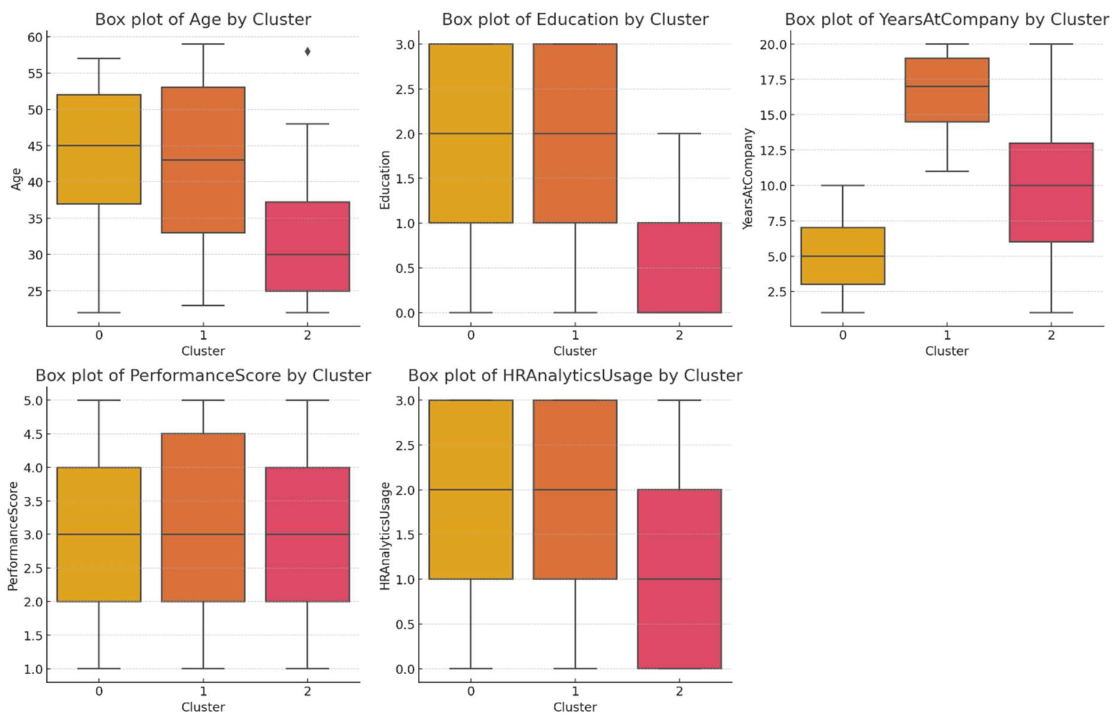

Figure 8. Cluster Analysis of Demographic and Professional Characteristics in the ITeS Industry

4. Conclusion

This study profiles 189 ITeS personnel demographically and professionally. The industry is gender balanced, with 50.3% males and 49.7% women. Youth dominates, with the majority under 30 and 31-40. This trend strongly signals industry growth. Most employees work in lower and middle management, with 23.3% in top management. This distribution shows a hierarchical industry with career routes. Nuclear families (58.2%) outweigh joint families (41.8%), reflecting societal family structure trends. Most sample members had undergraduate (43.4%) or postgraduate (28.6%) degrees, with few professional (17.5%) qualifications. This educational environment highlights ITeS management's importance of higher education. According to regression models, age and work experience predict management positions but not education. For instance, age inversely correlates with a management position, suggesting younger workers will climb. Industry veterans have lower management positions because work experience adversely corresponds with management positions. In ITeS, younger, less experienced workers advance faster to management positions. Exploratory and correlational data analyses show the study's demographic and occupational links. Seniors use HR analytics less despite their higher education. HR analytics users perform better, according to performance scores. This suggests integrating HR analytics into daily operations to improve employee performance. Factor study shows how age, HR analytics utilization, education, performance scores, and company years relate. These factors show worker tendencies, enabling HR customization. Cluster analysis separates workers into three needs-based groups. Cluster 0, somewhat older employees with moderate performance and HR analytics use, may need extra training. Cluster 1, with its top talent, including highly educated, experienced, and high-performing professionals, might mentor or lead HR analytics projects. In Cluster 2, younger, lower-educated professionals with moderate to high performance need additional training to realize their potential. This extensive study illuminates ITeS professionals and demographics. Age and work experience determine career growth, HR analytics boost performance, and different employee segments have different needs. These findings inform HR strategies to improve employee engagement, performance, and organizational effectiveness. HR analytics helps the ITeS industry understand and address its diverse workforce's needs, improving market success and competitiveness.

References

Agarwal, H., & Raj, V. J. P. (2022). Adoption of Human Resource Analytics in Information Technology and Information Technology Enabled Services Industry in India. *Journal of Data Science, Informetrics, and Citation Studies*, *1*(1). https://doi.org/10.5530/jcitation.1.1.7

Arora, M., Prakash, A., Mittal, A., & Singh, S. (2024). HR analytics: what's holding users back? *Global Knowledge, Memory and Communication*, *73*(3). https://doi.org/10.1108/GKMC-03-2022-0067

Awasthi, S., Bathla, D., & Singh, S. (2023). A Literature Review on HR Analytics: Trends and Future Challenges. In *The Adoption and Effect of Artificial Intelligence on Human Resources Management, Part B*. https://doi.org/10.1108/978-1-80455-662-720230014

Bulsari, S., & Pandya, K. (2023). Future of HR Analytics:s: Applications to Recruitment, Employee Engagement, and Retention. In *Managing Technology Integration for Human Resources in Industry 5.0*.

Cayrat, C., & Boxall, P. (2022). Exploring the phenomenon of HR analytics: a study of challenges, risks and impacts in 40 large companies. *Journal of Organizational Effectiveness*, *9*(4). https://doi.org/10.1108/JOEPP-08-2021-0238

Cho, W., Choi, S., & Choi, H. (2023). Human Resources Analytics for Public Personnel Management: Concepts, Cases, and Caveats. In *Administrative Sciences* (Vol. 13, Issue 2). https://doi.org/10.3390/admsci13020041

Dr Girisha H, Prajwal JM, Megha, R Abhishek, & Monika HK. (2023). Leveraging HR Analytics using Business Intelligence and Analytics. *International Journal of Advanced Research in Science, Communication and Technology*. https://doi.org/10.48175/ijarsct-9708

Elrehail, H. (2023). HR Analytics and Future of Work: A Systematic Literature Review. *2nd International Conference on Business Analytics for Technology and Security, ICBATS 2023*. https://doi.org/10.1109/ICBATS57792.2023.10111370

HR Analytics: Concept, Application, and Impact on Talent Management, Branding, and Challenges. (2023). *European Journal of Business and Management*. https://doi.org/10.7176/ejbm/15-8-06

Jana, B., & Kaushik, T. (2022). Application of technology-organization-environment model in HR analytics adoption. *Journal of Information and Optimization Sciences*, *43*(6). https://doi.org/10.1080/02522667.2022.2117331

Jha, S. (2022). Data Privacy and Security Issues in HR Analytics: Challenges and the Road Ahead. *Lecture Notes in Networks and Systems*, *209*. https://doi.org/10.1007/978-981-16-2126-0_17

Jiang, Y., & Akdere, M. (2021). An operational conceptualization of human resource analytics: implications for in human resource development. In *Industrial and Commercial Training* (Vol. 54, Issue 1). https://doi.org/10.1108/ICT-04-2021-0028

Kritz, M. V. (2017). From systems to organisations. *Systems*, *5*(1). https://doi.org/10.3390/systems5010023

Kurikala, V., & Parvathi, V. (2023). Identifying the Characteristics that Lead to Effective Data Analytics Deployment in Human Resource Management—A Paradigm for Consequences. *Journal of Chinese Human Resource Management*, *14*(1). https://doi.org/10.47297/wspchrmWSP2040-800503.20231401

Marler, J. H., & Boudreau, J. W. (2017). An evidence-based review of HR Analytics. *International Journal of Human Resource Management*, *28*(1). https://doi.org/10.1080/09585192.2016.1244699

Mukuze, K., Chavunduka, D., Manuere, F., & Ndhlovu, P. (2023). An Integrative Review of HR Analytics Implementation. *Management and Economics Research Journal*, *9*(1). https://doi.org/10.18639/merj.2023.9900076

Pandya, D. (2023). HR Analytics – Importance and Challenges. *INTERANTIONAL JOURNAL OF SCIENTIFIC RESEARCH IN ENGINEERING AND MANAGEMENT*, *07*(07). https://doi.org/10.55041/ijsrem24526

Peres, A. R., & Barbin Laurindo, F. J. (2023). *PATHWAYS FOR THE EVOLUTION OF HR ANALYTICS MATURITY: KNOWLEDGE CREATION AND ALIGNMENT WITH INFORMATION TECHNOLOGY*. https://doi.org/10.5748/19contecsi/pse/kmg/7048

Ratnam, D. S., & Devi, V. R. (2024). Addressing impediments to HR analytics adoption: guide to HRD professionals. *Human Resource Development International*, *27*(1). https://doi.org/10.1080/13678868.2023.2195986

Singh, T., Grewal, H. S., & Upadhyay, R. K. (2021). *A Model for Evaluating HR Analytics Critical Success Factors in Industry 5.0*. https://doi.org/10.4018/978-1-7998-8497-2.ch009

Tursunbayeva, A., Di Lauro, S., & Pagliari, C. (2018). People analytics—A scoping review of conceptual boundaries and value propositions. In *International Journal of Information Management* (Vol. 43). https://doi.org/10.1016/j.ijinfomgt.2018.08.002

Valecha, N. (2022). Transforming human resource management with HR analytics: A critical Analysis of Benefits and challenges. *International Journal for Global Academic & Scientific Research*, *1*(2). https://doi.org/10.55938/ijgasr.v1i2.16

Verma, S., Rana, N., & Meher, J. R. (2024). Identifying the enablers of HR digitalization and HR analytics using ISM and MICMAC analysis. *International Journal of Organizational Analysis*, *32*(3). https://doi.org/10.1108/IJOA-01-2023-3611

Wirges, F., & Neyer, A. K. (2023). Towards a process-oriented understanding of HR analytics: implementation and application. *Review of Managerial Science*, *17*(6). https://doi.org/10.1007/s11846-022-00574-0

Wright, P. M., & Mcmahan, G. C. (2011). Exploring human capital: Putting “human” back into strategic human resource management. *Human Resource Management Journal*, *21*(2). https://doi.org/10.1111/j.1748-8583.2010.00165.x

Zeidan, S., & Itani, N. (2020). HR analytics and organizational effectiveness. *International Journal on Emerging Technologies*, *11*(2).