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Organizational Culture Proxies, Employee Performance, and Business Productivity Evidence from HR Analytics Data

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ABSTRACT

This study investigates the relationship between organizational culture proxies, employee performance and business productivity, using HR analytics data. Measurable HR indicators were used such as job satisfaction, training hours, attendance, years of experience, monthly income and hours worked per week as an indicator of the culture of an organisation, which is not an easy indicator to measure. The study adopted quantitative, cross sectional and analytical research design of which the respondents were 10,000 employees. Descriptive statistics, Pearson correlation analysis, and multiple linear regression were used to assess the impact of organizational culture-related indicators on employee performance and productivity. Of these results, the most significant were job satisfaction, projects completed, number of years of experience, monthly salary, training hours, and attendance rate. A good model's predictive ability is demonstrated by the high percentage of the variance that is accounted for in this regression model, which is 87.01%. The difference between the two was not significant, suggesting that satisfaction, development, consistency and productivity had a greater effect on performance than increased work hours. The results confirm the effectiveness of HR Analytics as a source of evidence-based information regarding organization culture and employees' performance. This research contribute to HR analytics & organizational management literature because it demonstrate the importance of capturing data about employees' regular activities to consider culture in HR related issues and increase the productivity of business.

KEYWORDS: Organizational culture; HR analytics; Employee performance; Business productivity; Job satisfaction

1. Introduction

Organizational culture has become one of the most powerful factors that shape the behaviour of employees, organizational effectiveness and long-term business success. Positive organizational culture leads to employee engagement, collaboration, innovation and continuous learning among the employees, which in turn increases the productivity of employees and the competitiveness of the organization (Albrecht et al., 2018). Organizations have increasingly moved beyond intuition-based HRM practices towards decisions based on evidence in recent years, which is fueling the growth of Human Resource (HR) Analytics as a strategic management tool. HR analytics can help organizations convert all the data regarding their employees into actionable information that can be used for workforce planning, performance management, workforce development, and strategic business decisions (Boudreau & Cascio, 2017; Marler & Boudreau, 2017).

The HR analytics adoption has gained traction across different industries due to the digital revolution in HRM. Many businesses today depend on data-driven HR solutions to assess employee actions, track company efficiency and enhance management decisions (Fernandez & Gallardo-Gallardo, 2020). HR analytics has therefore expanded from descriptive reporting to becoming a strategic capability that can help an organization to remain competitive and perform sustainably (Minbaeva, 2018; Otoo, 2019). Workforce analytics has also been identified as a good tool for matching investments in workforce with the goals of an organization and its operations (Levenson, 2018).

Employee performance is one of the most important results of organisational culture as it has a direct impact on the productivity, innovation and financial performance of the organisation. Staff in positive organizational cultures, with high engagement, learning opportunities, recognition and manager support tend to have higher job performance and higher commitment to organizational goals (Albrecht et al., 2018; Wamba et al., 2017). In addition, employee engagement is recognized as an important link between organizational resources and innovative work behaviour and organizational effectiveness (Kwon & Kim, 2020). Moreover, research on strategic human resource management indicates that the ability of organizations created by good HR management has a significant impact on sustainable competitive advantage and better organizational results (Jiang & Messersmith, 2018).

HR analytics is also becoming increasingly common, which has prompted organizations to combine employee data with business performance metrics, helping managers determine what can

aid in productivity growth and organizational value creation (Margherita, 2022). In recent years, digital HR platforms and e-HRMs have become a powerful tool for organizations to increase the efficiency of their workforce, optimize HR processes, and increase the value of their businesses (Poba-Nzaou et al., 2020). Digital technologies and knowledge sharing spaces have also enhanced the learning capacity of the organisation and facilitated evidence-based management practices to improve the performance of the organisation (Cooke et al., 2021; Nisar et al., 2019). While there have been ethical issues and a cautionary approach towards correct use of people analytics, HR analytics initiatives are still growing in organisations due to their high strategic value (Giermindl et al., 2022). The increased use of data-driven organizational environments in supporting workforce development and organizational innovation can also be seen in the emerging digital collaboration technologies (E, 2025).

Previous studies have explored the link between organizational culture and employee performance in detail (Boudreau & Cascio, 2017; Levenson, 2018) and the strategic importance of HR analytics without taking organizational culture into account (Margherita, 2022). In parallel, employee engagement, strategic HRM, digital HR transformation and workforce analytics were investigated as important contributors to organizational performance (Jiang & Messersmith, 2018). Relatively few empirical studies, however, have studied organizational culture by measuring HR analytics proxy variables, and have analyzed their cumulative impact on employee productivity and organizational productivity. Additionally, there is not very much evidence about the capability of common HR analytics metrics job satisfaction, training engagement, attendance, work experience, productivity to be used as representations of organizational culture in forecasting business modeling.

This study aims to build an integrated empirical framework that considers HR analytics data to analyze the organizational culture proxies, employee performance, and business productivity. For this goal, the study aims at uncovering measurable proxy variables of organizational culture that are embedded in HR analytics data, analyzing their impact on employees' performance, understanding how employees' performance relates to business productivity, and understanding how HR analytics variables predict variations in employee performance and business productivity.

2. Methodology

2.1 Research Design

The study used quantitative, cross-sectional and analytical research design to examine the relationships between the organizational culture proxies, employee performance and business productivity based on HR analytics data. The quantitative method was selected to allow the measurement and quantification of organizational variables and to allow multiple constructs to be analyzed statistically. It was a cross sectional design since all observations took place at one point in time at which the organization could be seen in its current state and employee outcomes of the study could be measured. The analytical character of the research is aimed at revealing the importance of associations and predictive relationships between the indicators of organizational culture and indicators of the effectiveness of the organization, based on the results of empirical analysis.

2.2 Data Source

The data set used in the study was an HR analytical data set that contained organizational information related to employees (Abdullah, 2026). The data were organized to capture measurable aspects of the organization that reflected workplace culture, employee behaviour and organizational performance. By consolidating employee information, performance metrics, engagement scores, and workforce data into a single platform, HR analytics equips your organization with facts and figures that can empower evidence-based decision-making. Organizational, demographic and performance related variables have been included in the data set that allow an insight into the impact of culture related organizational practices on employee performance and business productivity in general. Use of quantitative organisational information guarantees suitability for statistical modelling and performance evaluation.

2.3 Variables of Study

Measuring organisational culture was done through proxy variables because it is not directly observable. These comprised job satisfaction, job involvement, training hours, recognition score, employee engagement, managerial support, learning opportunities, work environment, internal mobility, and collaboration index, which all indicated different facets of work culture and employee experiences. The employee performance was used as a mediator between organizational culture and outcomes. Overall organizational output (business productivity) was the dependent variable. Control variables included were demographic factors (age, gender, department, work experience, education, and job level).

2.4 Measurement of Variables

Standardized HR analytics indicators and organizational performance measures were used to measure the variables. A five-point Likert scale was used for evaluating the perception based constructs: a score of 1 meant strongly disagree, 2 meant disagree, 3 meant neutral, 4 meant agree and 5 meant strongly agree. Organizational data was used to collect objective information including training hours, internal mobility, and performance appraisal scores. Employee performance was measured using standardized assessment scores or an employee's performance index based on the assessment system. Productivity of business was measured with the help of productivity indices, departmental output measures, efficiency indicators or overall organizational performance (which is available in the data set). Where appropriate, continuous variables were centered and scaled to allow comparisons on different measurement scales.

2.5 Data Analysis

Quantitative statistical methods were used to analyse the data relevant to HR analytics research. Demographic characteristics and the distribution of the variables in the study were summarized and described with descriptive statistics including measures of central tendency and dispersion. Multi-item constructs were assessed for internal consistency with Cronbach's alpha, a reliability measure for analyzing multi-item constructs. Pearson correlation analysis was then conducted to investigate the relationships between organisational culture proxy variables, employee performance and business productivity. Multiple linear regression analysis was used to test the hypotheses. The first regression model examined the effect of the proxies of organizational culture on employee performance, while the second regression model examined the combined effect of organizational culture proxies and employee performance on business productivity, with the control variables being demographic. Significant differences were considered at 5% level. The analysis was done with Python statistics libraries.

2.6 Model Specification

The empirical framework assumes that organizational culture has a positive relationship with employee performance and employee performance has a positive relationship with business productivity. The first regression model regresses employee performance on employee satisfaction, job involvement, training hours, recognition score, employee engagement, managerial support, learning opportunities, work environment, internal mobility, collaboration index and demographic control variables. The second regression model predicts business productivity using the proxy variables for organizational culture, employee performance and the same set of

demographic controls as in the first regression. These models enable both direct and indirect effects of organizational culture on productivity to be evaluated.

3. Results

The HR analytics dataset included 10,000 employee records, with detailed data on employee characteristics, the organization, indicators of work, performance measures, and measures of productivity. Based on the study objectives, job satisfaction score, training hours, attendance rate, years of experience, monthly salary, work hours per week were used as proxy variables for organizational culture and employee performance score was used as a proxy variable for business productivity.

3.1 Descriptive Statistics

The descriptive statistics of the key variables that have been included in the study are presented in Table 1. The average employee age was 40.27 years ($SD = 10.97$), with an average work experience of 16.95 years ($SD = 10.95$). The average salary of the employees was USD 115,645.95 per month, and the average workload was 45.15 hours per week. The average was 12.49 projects completed per worker, suggesting a moderately productive organization. The HR analytics indicators also show that the employees had 39.09 hours of training on average, the attendance rate was 85.06% and the job satisfaction was a relatively high score ($M = 8.67$). The overall performance score was found to be 88.84, which is an average score and indicates that most of the employees performed well in the organisation. The relatively high mean scores for job satisfaction, attendance, and performance suggest a generally positive organizational climate (as presented in Table 1) and observed standard deviations were adequate for further inferential analysis.

Table 1. Demographic Profile of Respondents

Variable	N	Mean	Standard Deviation	Minimum	Maximum
Age	10,000	40.27	10.97	22.00	59.00
Years of Experience	10,000	16.95	10.95	1.00	39.00
Monthly Salary (USD)	10,000	115,645.95	38,242.45	30,026.00	179,990.00
Work Hours per Week	10,000	45.15	8.89	30.00	60.00
Projects Completed	10,000	12.49	6.89	1.00	24.00
Training Hours	10,000	39.09	23.20	0.00	79.00

Attendance Rate (%)	10,000	85.06	8.67	70.00	99.99
Job Satisfaction Score	10,000	8.67	1.55	2.09	10.00
Performance Score	10,000	88.84	15.09	40.00	100.00

The distribution of the employees' performance scores in an organization is shown in Figure 1. The histogram shows that the scores for the performance are clustered around higher scores, suggesting that more employees have higher scores than average. The distribution is also satisfactory for regression and correlation analysis, which is adequate.

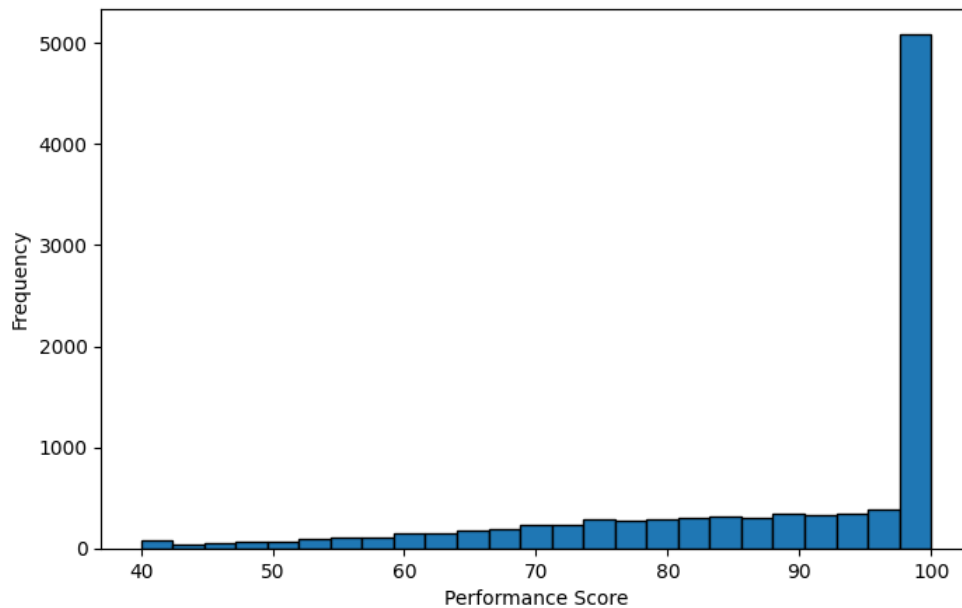


Figure 1. Distribution of Employee Performance Score

3.2 Correlation Analysis

Pearson correlation analysis was used to explore the correlations between the organization culture proxies, employee performance and business productivity. This summary of results is presented in Table 2. The highest positive correlation was found between job satisfaction and employee performance ($r = 0.865$) as shown in Table 2, which means that those employees who expressed higher levels of job satisfaction also generally had better levels of employee performance. The relationship of employee performance with business productivity (measured in terms of project completion) was also significant and positive ($r = 0.623$) and indicates that productive employees generally receive higher performance evaluations.

The years of experience had a moderate positive correlation ($r = 0.457$) and there were positive correlations with training hours ($r = 0.244$) and attendance rate ($r = 0.142$). In contrast, work hours per week had an almost insignificant correlation with employee performance ($r = 0.007$); that is, increasing work hours does not necessarily lead to greater employee effectiveness.

Table 2. Correlation Matrix among Organizational Culture Proxies, Employee Performance, and Business Productivity

Variable	Training Hours	Attendance Rate	Job Satisfaction	Work Hours	Experience	Projects Completed	Performance Score
Training Hours	1.000	0.008	0.207	-0.005	0.005	0.010	0.244
Attendance Rate	0.008	1.000	0.119	-0.007	-0.008	-0.010	0.142
Job Satisfaction Score	0.207	0.119	1.000	0.007	0.390	0.530	0.865
Work Hours per Week	-0.005	-0.007	0.007	1.000	0.007	0.004	0.007
Years of Experience	0.005	-0.008	0.390	0.007	1.000	0.020	0.457
Projects Completed	0.010	-0.010	0.530	0.004	0.020	1.000	0.623
Performance Score	0.244	0.142	0.865	0.007	0.457	0.623	1.000

As shown in Figure 2, there is a strong positive relationship between job satisfaction and employee performance. The scatter plot shows a clear positive relationship between job satisfaction and performance levels, indicating that higher employee satisfaction is associated with higher performance scores. The graphical evidence shows correlation evidence and strengthens the role of organizational culture in influencing employees' outcomes.

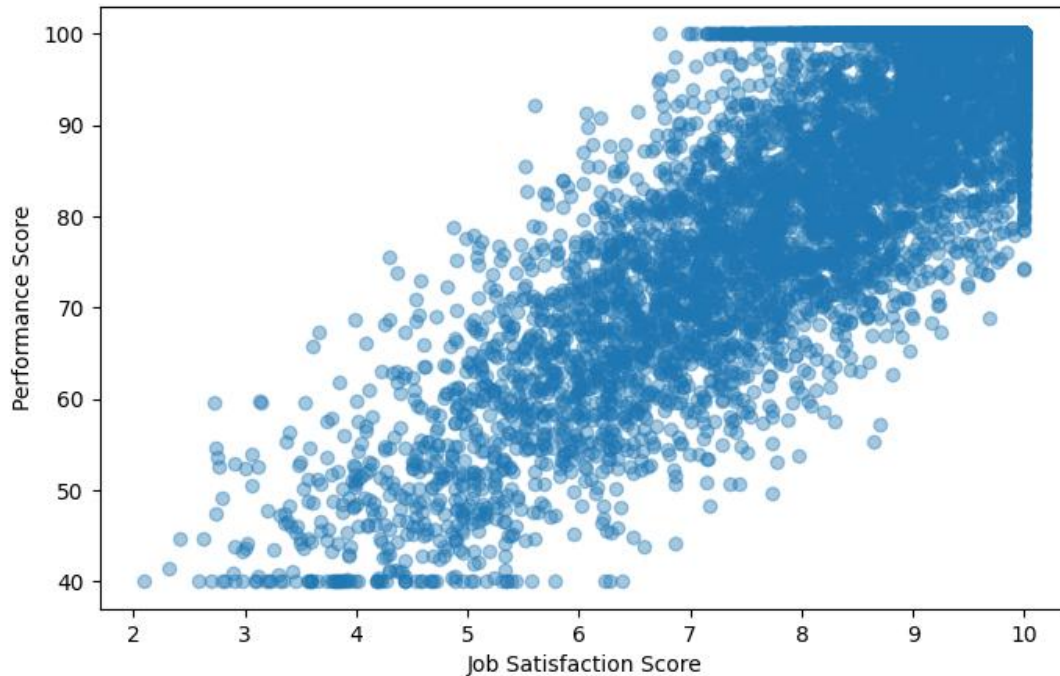


Figure 2. Relationship between Job Satisfaction Score and Employee Performance

3.3 Regression Analysis

Multiple linear regression was used to assess the impact of the proxy variables of organizational culture on employee performance. The estimated regression coefficients, standard errors, t-values and the significance are provided in Table 3. The regression model has an explanatory power of 87.01% ($R^2 = 0.8701$), which is excellent. The explanatory variable with the highest positive value was job satisfaction score ($\beta = 4.4365$, $p < 0.001$) indicating that employee satisfaction has a major impact on improving the performance outcomes.

Similarly, projects completed ($\beta = 0.5753$, $p < 0.001$), years of experience ($\beta = 0.2652$, $p < 0.001$), monthly salary ($\beta = 0.0001$, $p < 0.001$), attendance rate ($\beta = 0.1108$, $p < 0.001$), and training hours ($\beta = 0.0662$, $p < 0.001$) exerted statistically significant positive effects on employee performance. Work hours per week were not statistically significant ($p = 0.9363$) showing that longer working hours per week are not a significant factor in improving performance after controlling for other organizational factors.

Table 3. Multiple Regression Results Predicting Employee Performance

Predictor	Coefficient	Std. Error	t-value	p-value
Constant	15.2647	0.6577	23.2100	<0.001

Training Hours	0.0662	0.0024	27.0602	<0.001
Attendance Rate	0.1108	0.0064	17.3240	<0.001
Job Satisfaction Score	4.4365	0.0541	81.9454	<0.001
Work Hours per Week	-0.0005	0.0061	-0.0799	0.9363
Years of Experience	0.2652	0.0057	46.5951	<0.001
Projects Completed	0.5753	0.0100	57.6209	<0.001
Monthly Salary (USD)	0.0001	0.0000	50.3225	<0.001

Figure 3 shows that increased business productivity is associated with better employee performance. The scatter graph shows that the number of projects that employees finish is positively correlated with their performance score; the more projects employees finish, the higher their performance score. The graphical trend further confirms the regression results and emphasizes the significance of employee productivity in organisational performance.

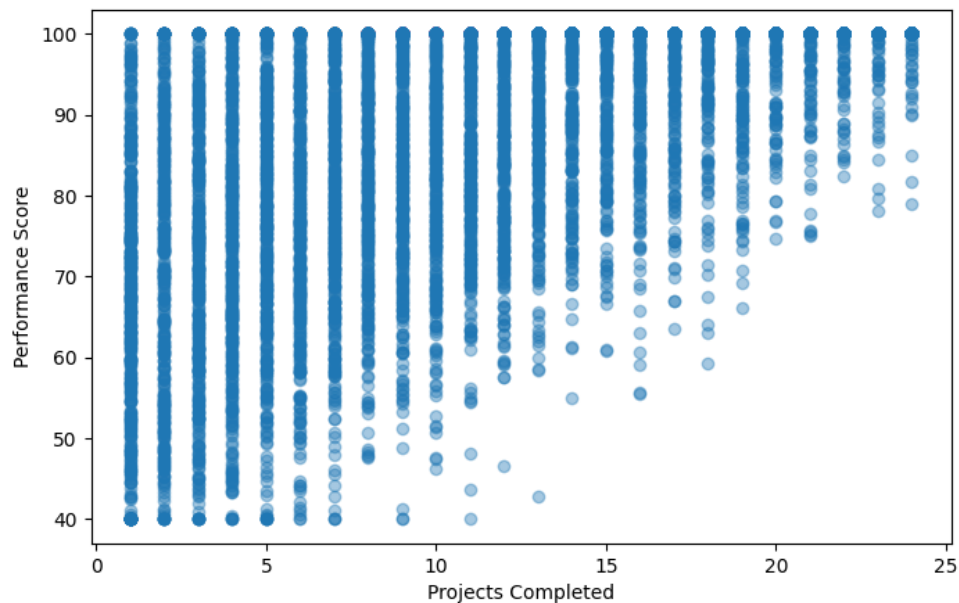


Figure 3. Relationship between Projects Completed and Employee Performance

3.4 Summary of Findings

Empirical results indicate that the organizational cultural proxy variables obtained through HR analytics data have a significant relationship with the employees' performance and the productivity of the business in general. Projects completed, years of experience, monthly salary, training hours,

and attendance rate were the next most influential on employee performance, with the latter being job satisfaction. However, after the other predictors were included in the model, work hours per week were not a significant factor in employee performance. The descriptive statistics, correlation analysis, regression analysis and the graphs all show that organisations that focus on employees' satisfaction, continuous learning, regular attendance and productive work practices have a higher chance of having higher employee performance and better business productivity. The findings confirm the study's key hypothesis: HR analytics offer a valid evidence-based approach to measure the organizational culture's effect on organizational success.

4. Discussion

Based on the findings of this research, it can be concluded that the variables of organizational culture proxies obtained from HR analytics data have a significant effect on employee performance and business productivity. Job satisfaction, projects completed, years of experience, attendance rate, training hours, and monthly salary were the most important predictors of employee performance. As digital HR systems and evidence-based management practices become more prevalent, they have enabled organizations to process employee data into strategic knowledge that aids in making more informed decisions (Bahuguna et al., 2023; Sharma et al., 2023). The results also confirm that digital skills and organisational agility are becoming paramount in the current context of work, and that digital management practices drive sustainable organisational performance (Espina-Romero et al., 2024; Wang et al., 2023).

A positive correlation between job satisfaction and employee performance was established indicating that supportive organizational environments are related to employee effectiveness. There is recent evidence that digital HRM systems can improve the efficiency of the workforce and the performance of the organization by creating a linking between staff information and strategic HR processes (Theres & Strohmeier, 2023). In the same way, constant learning of employees' competencies and digital skills allow companies to be competitive in the changing business environment (Sousa & Rocha, 2019).

The results further confirm that HR analytics is a valuable management support tool. The use of evidence-based management practices has been growing in organisations to enhance their planning, resource allocation and workforce optimisation (Sharma et al., 2023). It has also been seen that the development of HR analytics in recent years, such as predictive modelling, artificial

intelligence, and advanced workforce analytics, further emphasizes its use to enhance organizational decision-making (Bahuguna et al., 2023). These capabilities align with broader digital transformation efforts that promote the use of data for strategic decision-making processes (Espina-Romero et al., 2024).

The positive link between employee performance and projects completed implies that there is a direct relationship between employee performance and business productivity. Personnel who are trained regularly, more likely to attend and work in conducive environments can contribute to the organizations. The results also corroborate with those from the digital business transformation studies, which associate employee competencies and organizational learning with performance and innovation (Sousa & Rocha, 2019). The application of intelligent organizational systems, Industry 5.0 technologies, and cyber-physical integration can further boost productivity by optimizing working processes and the capacity of the working force (Wang et al., 2023). The strategic leadership competencies also contribute to organizational innovation and sustainable performance outcomes (Fayyad et al., 2025).

The findings are in line with past research on HR analytics and organizational performance. Recent studies have highlighted the role of HR analytics in business management, especially in the context of making informed workforce decisions (Bahuguna et al., 2023). Similarly, meta-analytical evidence of the positive impact of digital HRM on employee performance indicates positive outcomes at the organizational level because of digital HR practices (Theres & Strohmeier, 2023). The role of digital competencies also aligns with research findings that innovation and digital transformation are key factors in the competitiveness of organizations (Espina-Romero et al., 2024). The use of artificial intelligence in organization analytics can enhance the decision making process in various business functions (Bag et al., 2021) although AI has been investigated in customer engagement and marketing settings. Likewise, the investment in human capital, mentioned in this study, plays a significant role in ensuring the competitiveness and financial results of an organization, emphasizing the need to invest in human capital (Klimontowicz & Majewska, 2022).

The study suggests some managerial implications. HR managers should make employee satisfaction, training, attendance and career development as fundamental aspects of the organizational culture (Bag et al., 2021; Kumar et al., 2023). Workforce analytics can help inform evidence-based HR policies to enhance employee engagement, optimize resources and drive

ongoing organizational improvement. In the theoretical context, the study adds to the HR analytics and organizational behaviour literature by establishing that the organizational culture can be operationalized in terms of proxy HR analytic variables. On the practical side, it offers a way of evaluating organizational culture with information that is easily accessible to HR. Artificial Intelligence, deep learning, and advanced analytics are evolving technologies in various domains, and incorporating these into the HR decision-making process can increase the efficiency of the organization and sustainable business productivity.

5. Conclusion

The purpose of this study was to explore the impact of the HR analytics data derived proxy variables of organizational culture on employee performance and business productivity. The empirical results show that job satisfaction, training in hours, attendance rate, years of experience and projects completed in the job have significant impacts on employee performance, and work hours per week have no significant impact. Job satisfaction was the single strongest predictor of employee performance among all of the predictors examined, indicating that a positive organizational environment that fosters employees' engagement and well-being is important. The positive correlation between employees' performance and enterprise productivity also reflects that the better they perform, the better the enterprise does. The paper adds to the growing body of literature on HR analytics in that it shows that objective organizational indicators can be used to assess organizational culture in addition to just relying on subjective cultural assessments. This evidence supports the strategic use of HR analytics as a decision making instrument for assessing organisational performance, strengths and informing evidence-based HR interventions. Longitudinal data sets, use of more organizational culture dimensions, and industry and country comparisons may be used in future research to increase the generalizability of the proposed analytical framework. In summary, the study confirms that HR analytics offers a powerful tool for grasping the intricate dynamics between the organization's culture, employee productivity, and business productivity.

References

1. Abdullah, J. (2026). Employee Performance Metrics. <https://www.kaggle.com/datasets/jamiabdullah/employee-performance-metrics>

2. Albrecht, S., Breidahl, E., & Marty, A. (2018). Organizational resources, organizational engagement climate, and employee engagement. *Career Development International*, 23(1), 67–85. <https://doi.org/10.1108/CDI-04-2017-0064>
3. Bag, S., Srivastava, G., Bashir, M. M. A., Kumari, S., Giannakis, M., & Chowdhury, A. H. (2021). Journey of customers in this digital era: Understanding the role of artificial intelligence technologies in user engagement and conversion. *Benchmarking: An International Journal*, 29(7), 2074–2098. <https://doi.org/10.1108/BIJ-07-2021-0415>
4. Bahuguna, P. C., Srivastava, R., & Tiwari, S. (2023). Human resources analytics: Where do we go from here? *Benchmarking: An International Journal*, 31(2), 640–668. <https://doi.org/10.1108/BIJ-06-2022-0401>
5. Boudreau, J., & Cascio, W. (2017). Human capital analytics: Why are we not there? *Journal of Organizational Effectiveness: People and Performance*, 4(2), 119–126. <https://doi.org/10.1108/JOEPP-03-2017-0021>
6. Cooke, F. L., Dickmann, M., & Parry, E. (2021). IJHRM after 30 years: Taking stock in times of COVID-19 and looking towards the future of HR research. *The International Journal of Human Resource Management*, 32(1), 1–23. <https://doi.org/10.1080/09585192.2020.1833070>
7. E, N., Jill. (2025). Cultivating Creative Collaboration in Student Virtual Teams in Higher Education: Design and Climate: Design and Climate. IGI Global.
8. Espina-Romero, L., Ríos Parra, D., Noroño-Sánchez, J. G., Rojas-Cangahuala, G., Cervera Cajo, L. E., & Velásquez-Tapullima, P. A. (2024). Navigating Digital Transformation: Current Trends in Digital Competencies for Open Innovation in Organizations. *Sustainability*, 16(5), 2119. <https://doi.org/10.3390/su16052119>
9. Fayyad, S., Elsayy, O., Wafik, G. M., Abotaleb, S. A., Ali Abdelrahman, S. A., Abdel Moneim, A., Omran, R., Attia, S., & Mansour, M. A. (2025). Leaders' STARA Competencies and Green Innovation: The Mediating Roles of Challenge and Hindrance Appraisals. *Tourism and Hospitality*, 6(4), 202. <https://doi.org/10.3390/tourhosp6040202>
10. Fernandez, V., & Gallardo-Gallardo, E. (2020). Tackling the HR digitalization challenge: Key factors and barriers to HR analytics adoption. *Competitiveness Review*, 31(1), 162–187. <https://doi.org/10.1108/CR-12-2019-0163>
11. Giermindl, L. M., Strich, F., Christ, O., Leicht-Deobald, U., & Redzepi, A. (2022). The dark sides of people analytics: Reviewing the perils for organisations and employees. *European*

- Journal of Information Systems, 31(3), 410–435.
<https://doi.org/10.1080/0960085X.2021.1927213>
12. Jiang, K., & Messersmith, J. (2018). On the shoulders of giants: A meta-review of strategic human resource management. *The International Journal of Human Resource Management*, 29(1), 6–33. <https://doi.org/10.1080/09585192.2017.1384930>
 13. Klimontowicz & Majewska,. (2022). The contribution of intellectual capital to banks’ competitive and financial performance: The evidence from Poland. *Journal of Entrepreneurship, Management and Innovation*, 18(2), 105–136.
 14. Kumar, V., Azamathulla, H. M., Sharma, K. V., Mehta, D. J., & Maharaj, K. T. (2023). The State of the Art in Deep Learning Applications, Challenges, and Future Prospects: A Comprehensive Review of Flood Forecasting and Management. *Sustainability*, 15(13), 10543. <https://doi.org/10.3390/su151310543>
 15. Kwon, K., & Kim, T. (2020). An integrative literature review of employee engagement and innovative behavior: Revisiting the JD-R model. *Human Resource Management Review*, 30(2), 100704. <https://doi.org/10.1016/j.hrmr.2019.100704>
 16. Levenson, A. (2018). Using workforce analytics to improve strategy execution. *Human Resource Management*, 57(3), 685–700. <https://doi.org/10.1002/hrm.21850>
 17. Margherita, A. (2022). Human resources analytics: A systematization of research topics and directions for future research. *Human Resource Management Review*, 32(2), 100795. <https://doi.org/10.1016/j.hrmr.2020.100795>
 18. Marler, J. H., & Boudreau, J. W. (2017). An evidence-based review of HR Analytics. *The International Journal of Human Resource Management*, 28(1), 3–26. <https://doi.org/10.1080/09585192.2016.1244699>
 19. Minbaeva, D. B. (2018). Building credible human capital analytics for organizational competitive advantage. *Human Resource Management*, 57(3), 701–713. <https://doi.org/10.1002/hrm.21848>
 20. Nisar, T. M., Prabhakar, G., & Strakova, L. (2019). Social media information benefits, knowledge management and smart organizations. *Journal of Business Research*, 94, 264–272. <https://doi.org/10.1016/j.jbusres.2018.05.005>
 21. Otoo, F. N. K. (2019). RETRACTED: Human resource development (HRD) practices and banking industry effectiveness: The mediating role of employee competencies. *European*

- Journal of Training and Development, 43(3–4), 250–271. <https://doi.org/10.1108/EJTD-07-2018-0068>
22. Poba-Nzaou, P., Uwizeyemunugu, S., Gaha, khadija, & Laberge, M. (2020). Taxonomy of business value underlying motivations for e-HRM adoption: An empirical investigation based on HR processes. *Business Process Management Journal*, 26(6), 1661–1685. <https://doi.org/10.1108/BPMJ-06-2018-0150>
 23. Sharma, S. K., Goyal, P., & Chanda, U. (2023). *Handbook of Evidence Based Management Practices in Business*. Taylor & Francis.
 24. Sousa, M. J., & Rocha, Á. (2019). Skills for disruptive digital business. *Journal of Business Research*, 94, 257–263. <https://doi.org/10.1016/j.jbusres.2017.12.051>
 25. Theres, C., & Strohmeier, S. (2023). Met the expectations? A meta-analysis of the performance consequences of digital HRM. *The International Journal of Human Resource Management*, 34(20), 3857–3892. <https://doi.org/10.1080/09585192.2022.2161324>
 26. Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research*, 70, 356–365. <https://doi.org/10.1016/j.jbusres.2016.08.009>
 27. Wang, X., Yang, J., Wang, Y., Miao, Q., Wang, F.-Y., Zhao, A., Deng, J.-L., Li, L., Na, X., & Vlacic, L. (2023). Steps Toward Industry 5.0: Building “6S” Parallel Industries With Cyber-Physical-Social Intelligence. *IEEE/CAA Journal of Automatica Sinica*, 10(8), 1692–1703. <https://doi.org/10.1109/JAS.2023.123753>