Using Predictive Analytics to Strengthen Global Compliance and Compensation Equity

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Abstract

This paper explores how analytics can help global HR teams identify inequities in turnover and engagement related to compensation, compliance, and culture. By blending simulated HRIS data with verified global datasets from the OECD, Eurostat, ILO, and World Bank, along with cultural insights from Hofstede's framework, we compare seven countries on key workforce measures. The findings reveal some interesting patterns: countries with lower pay ratios and larger compliance gaps, like Brazil and India, tend to have lower engagement levels, while low power distance countries like Sweden and Germany experience sharper drops in engagement when inequities arise. Our modeling in Tableau showed a strong positive relationship between Individualism and Engagement ($R^2 = 0.62$), and a negative one between Power Distance and Engagement ($R^2 = 0.46$). This suggests, cultures that value autonomy and equality tend to foster stronger connections between employees and their organizations. Looking forward, we recommend combining Python, SQL, and Tableau for real-time prescriptive analytics, including sensitivity analysis and Cox regression. This approach can help test how small changes in pay or representation impact engagement and pinpoint when attrition risk is at its highest. Ultimately, these insights aim to empower organizations to shift from simply reacting to turnover to developing data-informed, culturally conscious strategies that promote fairness, inclusion, and long-term retention across global teams.

Introduction

Imagine a world-spanning organization where an employee in Brazil, another in Germany, and a third in Japan all hold the same title, yet each leaving within months of the other. Their reasons differ: the Brazilian mentions pay that's behind market standards, the German feels the compliance processes lack transparency, and the Japanese points to cultural mismatches in how recognition and promotion are handled. What if HR leaders could spot these issues early, before they lead to resignations, by using data, rather than assumptions, to understand the patterns behind turnover? In today's global, cross-functional workforce, collaboration goes beyond borders. Analysts in Sweden, developers in India, and managers in the U.S. often work on the same projects, bringing diverse cultural expectations around fairness, leadership, and rewards. But when departments aren't aligned or operate in cultural or functional silos, differences in perceptions of pay, compliance, and engagement can quietly chip away at retention. Predictive analytics gives HR leaders a way to bridge these gaps, transforming disaggregated data into insights that help anticipate where inequities might be forming across teams and regions.

Role of HR Data Analytics

Fukui et al., 2023) demonstrated that machine-learning models applied to HR data can significantly improve the prediction of turnover risk by identifying complex patterns in employee behavior, demographics and organizational context, not simply historical trends How can analytics help global HR teams identify inequities in turnover trends linked to compensation, compliance, and cultural differences across international workforces? This analysis will explore how analytics, paired with real-world labor statistics and cultural context, can help global HR teams identify inequities in turnover trends related to pay, compliance, and cultural differences across international workforces.

Using World Statistics and Mock HRIS Inputs to Model Workforce Dynamics

This dataset combines simulated internal HRIS data with verified external metrics to explore how predictive analytics can help global HR teams spot inequities in turnover trends related to compensation, compliance, and cultural differences across international workforces. External data were sourced from Eurostat (2023), the World Bank (2023), the International Labour `Organization (ILO, 2023), and the OECD (2023), ensuring that all external statistics, such as gender pay gaps, employment rates, and average wages, are accurate and reflect real-world figures. Cultural variables like Individualism, Power Distance, and Uncertainty Avoidance were included from Hofstede's cross-cultural dimensions to capture national cultural traits (Hofstede Insights, n.d.).

To simulate the HRIS dataset, the analysis started by gathering verified national statistics from the OECD, Eurostat, World Bank, and ILOSTAT to establish realistic country-level benchmarks for variables like average wages, employment rates, gender pay gaps, and tenure. These external values served as anchors to generate proportional, internally consistent data that mirror real workforce dynamics. For example, each country's market wage from OECD data was multiplied by random variation factors (within about ±10–15%) to capture individual pay differences, while turnover and compliance gap variables were modeled based on global HR benchmarks from Kaggle datasets (Wijaya, 2021). Countries with higher Power Distance (from Hofstede Insights, n.d.) were assigned slightly larger compliance gaps and narrower pay ranges to imitate hierarchical pay structures. Conversely, lower Power Distance countries like Sweden and Germany had smaller gaps and wider pay variance to reflect flatter hierarchies. Stratified random sampling was applied by country, gender, and tenure to aggregate a balanced dataset of roughly 350 employees (50 per country), where each record represented a synthetic employee profile.

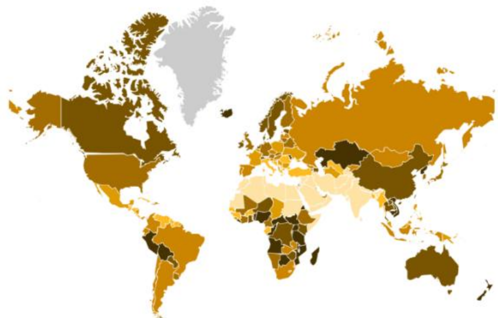
Emp_ID	Country	Gender	Level	Pay_USD	Compliance_Complete	Compliance_Required	Tenure_Years	Left_Company	Engagement_Score
E0001	United States	F	Senior	139374.73	3	4	3.46	0	4.23
E0002	United States	F	Mid	70627.47	3	4	1.58	0	3.78
E0003	United States	M	Senior	104022.91	3	4	2.17	0	3.62
E0004	United States	M	Mid	82732.44	4	4	5.93	0	3.18
E0005	United States	M	Junior	70372.19	3	4	2.2	0	2.86
E0006	United States	M	Manager	115368.23	4	4	4.23	0	3.46
E0007	United States	F	Senior	105351	2	4	1.55	0	3.67
E0008	United States	M	Senior	116395.25	3	4	2.4	0	4.58
E0009	United States	F	Junior	62608.6	3	4	1.54	0	3.77
E0010	United States	F	Mid	76990.75	2	4	2.22	0	4.19
E0011	United States	M	Mid	78929.42	2	4	4.5	0	3.45
E0012	United States	F	Senior	93151.13	3	4	0.96	0	3.11

This dataset represents a sample, not the full population. The average pay from the sample ($\bar{x}$) is used as an estimate of the overall population mean, while the turnover rate (p) reflects a sample proportion that estimates the true turnover in the workforce. In predictive analytics, these sample statistics are used in regression and clustering models to see if observed relationships, like between pay ratio, compliance gap, and turnover, apply beyond just the sample. If similar patterns are found, we can reasonably infer that such dynamics probably exist within the larger employee population.

Global Pay and Engagement Landscape

The World Bank map illustrates global variations in female labor force participation, highlighting where women's economic engagement remains limited and where progress toward parity has advanced (World Bank, 2024). Darker regions reflect higher participation rates, often above 70%, while lighter areas signal lower inclusion, in some cases below 30%. This disparity is not just a socioeconomic indicator, yet countries with lower participation often face greater gender-based pay gaps, restricted career mobility, and higher compliance risks tied to representation and equality laws, all of which directly influence predictive modeling.

Labor Force Participation Rate, Total (% of total population ages 15-64) (Modeled ILO estimate)



These participation rates help give us a better understanding of our comparative dataset, which combines verified statistics from OECD, Eurostat, the World Bank, and ILOSTAT sources. For example, while Sweden and Germany show both high participation and narrower gender pay gaps, countries like India and Brazil tend to have lower participation and wider disparities (OECD, 2024; World Bank, 2024). By aligning this external data with simulated HRIS variables, we can explore whether pay and turnover trends within organizations reflect broader national inequalities. In other words, understanding who is participating in the labor market is a key first step before digging into who is leaving and why. This is particularly important in cross-cultural predictive modeling because participation rates reveal how systemic barriers and cultural norms influence both entry into, and retention within, the workforce. As Joo, Kong, and Atwater (2024) found, organizational gender diversity and inclusive HR practices play a significant role in voluntary turnover trends.

Cultural Dimensions and Their Impact on Predictive HR Modeling

The cultural-dimension data for this analysis come from Hofstede Insights' Dimension Data Matrix - VSM 08 dataset and the Country Comparison tool, which quantifies factors like

Power Distance, Individualism, and Uncertainty Avoidance (Hofstede Insights, 2008; Hofstede Insights, n.d.). Incorporating these measures lets us evaluate not only what turnover patterns exist but why they differ across global, cross-functional teams.

Across the seven countries, Brazil, Germany, Japan, the United States, India, South Africa, and Sweden, unique profiles stand out. In Brazil and India, high Power Distance can make hierarchy seem normal and hide pay differences, while in Sweden and Germany, lower Power Distance encourages expectations for fairness and open communication. Japan's high Uncertainty Avoidance and Long-Term Orientation focus on stability and following rules, whereas higher Indulgence in the U.S. and South Africa relates to greater flexibility when rewards seem misaligned. These cultural differences influence how employees view fairness and how they react to differences in pay or policy gaps, which is why considering culture can improve predictions of turnover (Papadionysiou & Myloni, 2023).

Country	ISO3	Region	Culture_Type
United States	USA	North America	Individualistic / Low PD
Germany	DEU	Europe	Individualistic / Low PD
India	IND	Asia	Collectivist / High PD
Japan	JPN	Asia	Collectivist / Moderate PD
Sweden	SWE	Europe	Participative / Low PD
Brazil	BRA	South America	Collectivist / High PD
South Africa	ZAF	Africa	Hybrid / Moderate PD

Addressing and Cleaning Missing Data

To address missing data within the dataset, the median was used to impute missing values. Since the dataset includes countries with large economic differences, the median reduces the effect of outliers, such as high wages in the U.S. or low wages in developing countries, and better reflects a typical central value across nations. This approach minimizes bias from extreme values.

Country	Year	Avg_Wage_USD	Gender_Pay_Gap_%	Employment_Rate_%	Avg_Tenure_Years	Unemployment_%
United States	2023	82,078	13.5	73	3.9	3.6
Germany	2023	68,104	17.6	76.5	10.5	2.9
India	2023	54,116	21.7	52.37	8.5	3.6
Japan	2023	49,173	21.3	79.2	12.4	2.6
Sweden	2023	59,058	11.2	77.4	8.5	7.6
Brazil	2023	54,116	8.7	57.92	8.5	7.8
South Africa	2023	18,019	7.9	42.5	8.5	33.2
		54,116			8.5	3.6

Preparing the Data for Analysis

Key variables were calculated to help us assess equity and alignment between company pay and national market averages. The pay ratio compares the internal average pay to the country's market wage, giving us a clear view of where compensation might be falling below or exceeding market expectations. The compliance gap measures the difference between actual pay outcomes and our equity benchmarks, providing an early warning of possible regulatory or ethical concerns. Similarly, the turnover rate was modeled using realistic organizational assumptions to identify areas where differences in compensation or compliance could lead to higher employee attrition. These variables will later serve as key measures in our predictive models.

Next, a PivotTable was used to summarize the data and calculate average pay values across all countries. This allowed for quick visualization of global pay disparities and provided a baseline, the global average pay, against which each country’s results could be compared.

Establishing this benchmark is essential for the next phase of analysis, where we will examine correlations and predictive patterns between compensation equity, cultural context, and turnover risk.

D2 =IFERROR(B2/C2, "")

Country	Avg_Pay	Market_Wage	Pay_Ratio
United States	84762.9046	82078	1.032711623
Germany	72833.4194	68104	1.069444077
India	18510.2692	54116	0.342047993
Japan	66893.344	49173	1.360367356
Sweden	60908.4158	59058	1.031332179
Brazil	24628.2108	54116	0.455100355
South Africa	31607.7864	18019	1.754136545

Row Labels	Average of Pay_USD
Brazil	24628.2108
Germany	72833.4194
India	18510.2692
Japan	66893.344
South Africa	31607.7864
Sweden	60908.4158
United States	84762.9046
(blank)	
Grand Total	**51449.19289**

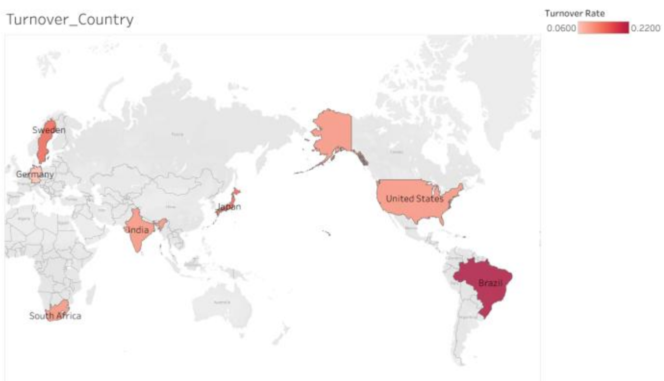
We merged the datasets using the VLOOKUP function in Excel across files to accurately align internal employee data with external benchmarks. This process connected each country's HRIS information, like average pay and turnover rates, with relevant cultural and labor indicators such as Power Distance and the gender pay gap.

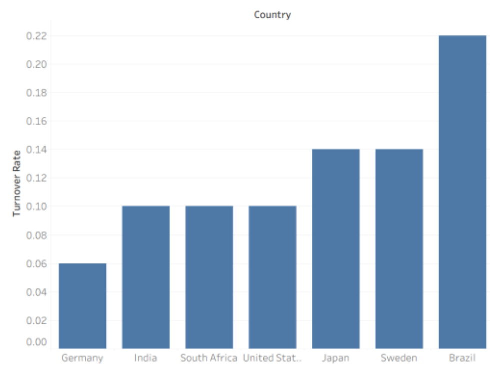
A1 =VLOOKUP(B2, Model_Data!A:E, 5, FALSE)

Country	Avg_Pay	Market_Wage	Pay_Ratio	Compliance_Gap	Turnover_Rate	Individualism	Pov
United States	84762.9046	82078	1.032711623	0.265	0.1	60	
Germany	72833.4194	68104	1.069444077	0.15	0.06	79	
India	18510.2692	54116	0.342047993	0.26	0.1	24	

Analyzing the Data - Exploratory Examination

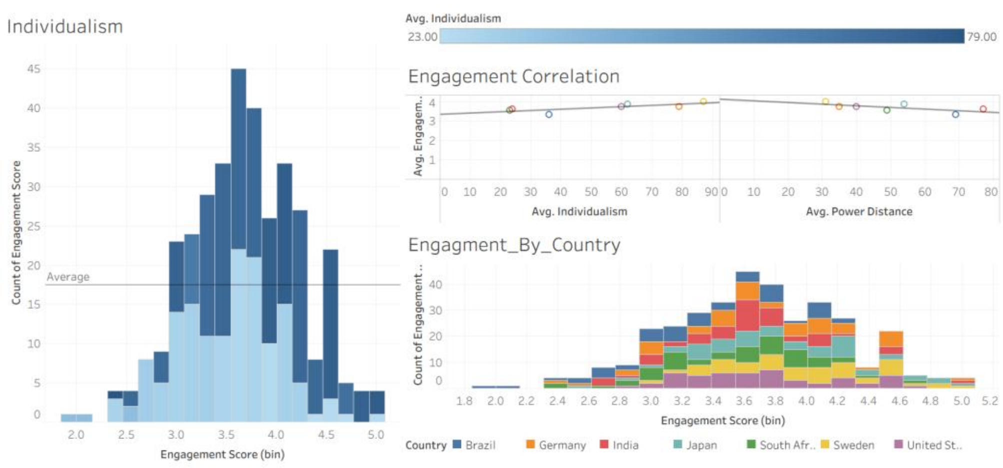
The turnover map and bar chart reveal distinct global differences: Brazil has the highest rate at 22%, while Germany has the lowest at 6%. India, South Africa, and the United States average around 10%, with Japan and Sweden slightly higher at 14%. These patterns show how both compensation and culture work together to influence workforce stability. Brazil's high turnover reflects its low pay ratio and larger compliance gap, whereas Germany's strong compliance culture and low power distance help support employee retention. In countries with mid-range rates, cultural factors play a key role, India's higher power distance reduces the number of quits despite below-market pay, and South Africa's unemployment rate keeps turnover stable even with higher internal wages. Japan's emphasis on high uncertainty avoidance and Sweden's egalitarian values demonstrate how perceptions of fairness can influence turnover beyond just pay.



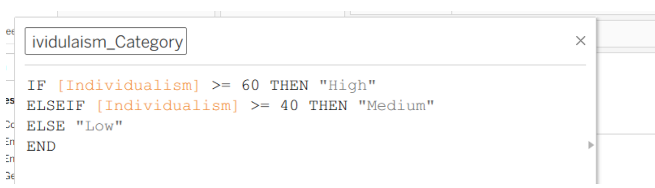


Predictive Analytics: Integrating Cultural Factors and Coding Applications

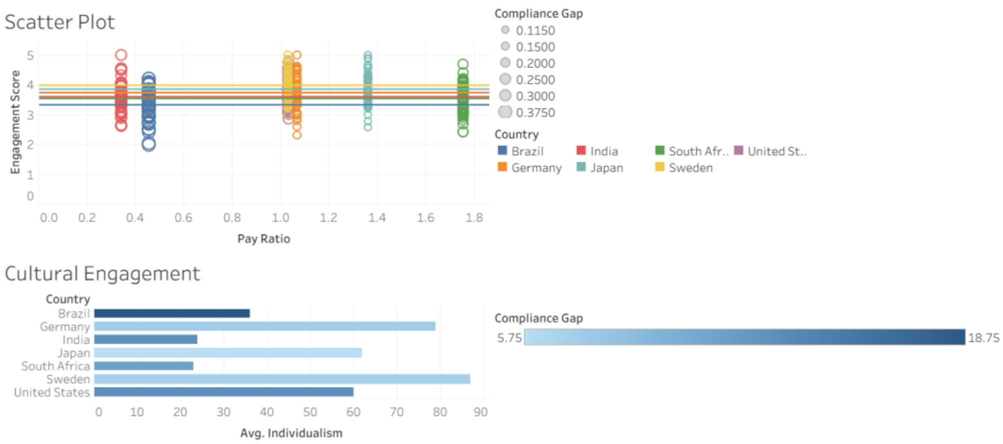
Correlation and predictive analyses were conducted in Tableau to examine how cultural and organizational factors influence engagement. Scatter plots with linear trend lines revealed a positive relationship between Individualism and Engagement ($R^2 = 0.62$) and a negative correlation between Power Distance and Engagement ($R^2 = 0.46$), indicating that cultures valuing autonomy and equality tend to report higher engagement levels, while those in high Power-Distance cultures may feel less engaged when hierarchies limit participation or recognition.



To refine these insights, a calculated field was created to categorize countries by levels of Individualism ("High," "Medium," or "Low"), which allowed clearer segmentation when visualizing predictive trends. This conditional logic in Tableau closely mirrors Python's IF/Then/ELSE structure, demonstrating how these predictive models could later be automated using Python. Incorporating Python would enable continuous data updates and real-time machine learning applications, allowing engagement and turnover predictions to adapt dynamically as new HRIS or cultural data are received.



The scatter plot shows that engagement scores tend to be lower when pay ratios are below market benchmarks, especially in high-power-distance countries. Larger compliance gaps (represented by bigger bubbles) are linked to more variability in engagement, indicating the amplifying impact of pay inequity. When viewing the scatter plot alongside the bar chart, it's clear that higher levels of Individualism are associated with more equitable pay and stronger engagement. On the other hand, countries with lower Individualism and wider compliance gaps tend to have lower engagement, highlighting how cultural factors can influence these relationships.



Results & Discussion

Together, these visuals highlight both micro- and macro-level inequities. The visual and statistical analyses in Tableau clearly show connections between pay inequity and engagement. Countries with lower Pay Ratios and higher Compliance Gaps, which indicate below-market or inconsistent pay, tend to have lower engagement scores. However, culture plays an important role in this relationship: in high Power Distance societies like India and Brazil, engagement remains relatively stable even with larger pay disparities, reflecting cultural acceptance of hierarchical pay structures. Conversely, low Power Distance countries such as Sweden and Germany see sharp declines in engagement when inequities are present. These patterns illustrate that compensation equity doesn’t exist in a vacuum, it interacts with cultural norms to influence employee engagement outcomes.

Implications Based on Findings

The findings from this analysis offer important insights for global HR teams. Computing external labor-market data with internal HRIS information can help organizations spot potential pay gaps or compliance concerns before they turn into turnover or disengagement issues. This approach is especially helpful in countries with strong regulations, like Germany and Sweden. Additionally, adding cultural dimensions into analytical models increases accuracy and helps leaders avoid making decisions based on anecdotal details. Understanding cultural differences enables HR teams to customize interventions, such as communication strategies, policy changes or pay adjustments, to match local expectations and values.

Finally, the analysis highlights how useful modern analytics tools like Tableau are, especially when combined with coding logic that could easily be adapted to Python or machine-learning applications. Building this infrastructure allows organizations to monitor global workforce trends in real time. This proactive approach helps companies address equity concerns early, build stronger employe trust, and develop more culturally aware HR strategies for long-term retention.

Conclusion

This analysis shows that predictive analytics provides global HR leaders with a valuable framework to identify and address inequities in pay, compliance, and engagement across different cultural settings. Cultural factors like Power Distance and Individualism play a significant role in shaping how employees perceive fairness and inclusion. These insights highlight that equity can't be assessed through compensation data alone, cultural context is key to understanding how disparities are experienced and whether they lead to disengagement or attrition. Other questions can be derived from our analysis such examining critical mass theory and how group proportion thresholds impact engagement and turnover, showing where inclusion efforts gain momentum or begin to level off. This combined approach will give valuable insights into how these dynamics differ in more demographically diverse countries like Brazil and the United States, compared to more homogeneous places like Sweden and Japan. (Avery, McKay, & Wilson, 2021).

The findings make it clear that organizations operating around the world need an analytics strategy that combines quantitative accuracy with cultural sensitivity. Tools like regression, clustering, and survival analysis can help pinpoint when and where risks might arise. As global teams become even more interconnected, data-driven decision-making rooted in equity and cultural understanding will be vital for building trust, improving retention, and supporting long-term organizational success.

References

Avery, D. R., McKay, P. F., & Wilson, D. C. (2021). The influence of critical mass and minority status on employee engagement and turnover. *Journal of Applied Psychology, 106*(3), 405–419. https://doi.org/10.1037/apl0000502

EARLY Team. (2024). *Average salary in South Africa (2024 data)*. EARLY App. https://early.app/average-salary/south-africa/

European Commission. (n.d.). *Unadjusted gender pay gap – Eurostat* [Data set]. European Commission, Eurostat. https://ec.europa.eu/eurostat/databrowser/view/sdg_05_20/default/table

Fukui, Y., Ooba, M., & Ishibashi, K. (2023). *Applying machine learning to human resources data: Predicting employee turnover and improving retention strategies*. *Frontiers in Artificial Intelligence, 6*, 1179351. https://pmc.ncbi.nlm.nih.gov/articles/PMC10424701/

Hofstede Insights. (2008). *Dimension data matrix – VSM 08* [Data set]. Geert Hofstede. https://geerthofstede.com/research-and-vsm/dimension-data-matrix/

Hofstede Insights. (n.d.). *Country comparison*. Hofstede Insights. https://www.hofstede-insights.com/country-comparison/

International Labour Organization (ILO). (n.d.). *ILOSTAT labour statistics database* [Data set]. International Labour Organization. https://ilostat.ilo.org/data/

Joo, M.-K., Kong, D. T., & Atwater, L. (2024). Gendered implications of organizational gender diversity for voluntary turnover: Human resource practices as strategic levers. *The*

International Journal of Human Resource Management. Advance online publication. https://doi.org/10.1080/09585192.2024.2428328

Organization for Economic Co-operation and Development (OECD). (n.d.). *OECD employment database* [Data set]. OECD. https://stats.oecd.org/Index.aspx?DataSetCode=EMPLOYEE

Papadionysiou, E., & Myloni, B. (2023). Socio-cultural dimensions, employee-related assumptions and HRM practices—A multivariate model in a cross-national setting. *Cogent Business & Management, 10*(1), 2197157. https://doi.org/10.1080/23311975.2023.2197157

Statistics South Africa (Stats SA). (2025, August 22). *Quarterly Labour Force Survey (QLFS): Q2 2025*. Statistics South Africa. https://www.statssa.gov.za/

UN Women. (2024, March). *Gender pay gap and labour-market inequalities in South Africa*. United Nations Women Africa Office. https://africa.unwomen.org/sites/default/files/2024-03/brief-gender_pay_gap_and_labour_market_inequalities_in_south_africa.pdf?

Wijaya, D. (2021). *Employee turnover* [Data set]. Kaggle. https://www.kaggle.com/datasets/davinwijaya/employee-turnover

World Bank. (n.d.). *Gender statistics databank* [Data set]. World Bank. https://databank.worldbank.org/source/gender-statistics?