European Journal of Hospitality and Tourism Research, 14(1),12-29, 2026
Print ISSN: ISSN 2054-6424(Print),
Online ISSN: ISSN 2054-6432(Online)
Website: https://www.eajournals.org/
Publication of the European Centre for Research Training and Development -UK

Human Resource Analytics and Employee Engagement in Selected Hospitality Firms in Lagos State, Nigeria

[1]S.S. Ojeyemi, [2] O. U.Egbuta, [3] V.O. Akpa and [4]G.K. Nnorom
[123]Department of Business Administration and Marketing, Babcock University, Ilishan-Remo, Ogun State, Nigeria
[4]Department of Business Administration, Caleb University, Imota, Lagos State, Nigeria

doi: https://doi.org/10.37745/ejhtr.2013/vol14n11229 Published April 14, 2026

Citation: Ojeyemi, S.S., Egbuta, O. U., Akpa, V. O., and Nnorom, G. K (2026) Human Resource Analytics and Employee Engagement in Selected Hospitality Firms in Lagos State, Nigeria, *European Journal of Hospitality and Tourism Research*, 14(1),12-29

Abstract: *Employee engagement remains a critical challenge in Nigeria's hospitality industry, with declining morale, high turnover, and service quality concerns despite increasing adoption of Human Resource Analytics (HRA). This study examined the effect of HRA on employee engagement in selected five-star hotels in Lagos State, Nigeria. A cross-sectional survey design was employed, with data collected from 394 employees across five prominent hotels using a structured questionnaire. Multiple regression analysis revealed that HRA significantly predicted employee engagement ($R = 0.608$; Adj. $R^2 = 0.362$; $F(5,388) = 45.603$, $p < 0.05$). Specifically, descriptive analytics ($\beta = 0.642$, $t = 4.010$, $p < 0.05$), predictive analytics ($\beta = 0.702$, $t = 5.036$, $p < 0.05$), and prescriptive analytics ($\beta = 1.067$, $t = 6.628$, $p < 0.05$) demonstrated significant positive effects, while diagnostic and operational analytics were non-significant. The findings indicate that approximately 36.2% of variance in employee engagement is explained by HRA practices, with prescriptive analytics emerging as the strongest predictor. The study concludes that strategic implementation of HRA significantly enhances employee engagement in the Nigerian hospitality sector, recommending that hoteliers prioritise predictive and prescriptive analytics capabilities to foster workforce commitment and service excellence.*

Keywords: human resource analytics, employee engagement, descriptive analytics, predictive analytics, prescriptive analytics, hospitality industry, Nigeria

INTRODUCTION

Employee engagement has emerged as a strategic imperative in the global hospitality industry, where workforce commitment directly influences service quality, customer satisfaction, and organisational performance (Andriani et al., 2023; Bansal et al., 2025). Engagement encompasses cognitive, emotional, behavioural, voice, and social dimensions through which employees invest psychologically in their work roles (Islam & Alam, 2024). However, hospitality organisations worldwide face persistent challenges in sustaining engagement, with Gallup (2024) reporting a decline in global employee engagement from 23% to 21%, representing an estimated $438 billion in productivity losses. In the United States, engagement levels dropped to a decade-low of 31% in 2024, while the United Kingdom reported that 42% of hospitality workers consider leaving the sector entirely (Dooley, 2025; Harri, 2023).

The African hospitality sector has not been immune to these trends. Agina et al. (2023) documented declining worker energy, loyalty, and commitment across the continent, with employees often feeling undervalued and excluded from decision-making processes. In Nigeria, Atolagbe et al. (2024) found that emotional engagement in Abuja's hospitality firms decreased from 68% in 2022 to 55% in 2024, while Adesunloye et al. (2024) reported declines in job satisfaction from 72% to 60% in Oyo State. These challenges are exacerbated by political instability, economic constraints, and governance issues that intensify workplace stress and contribute to disengagement (Adepoju et al., 2024).

Human Resource Analytics (HRA) has been proposed as a strategic mechanism for addressing engagement challenges through data-driven insights into workforce dynamics. HRA encompasses diagnostic, descriptive, operational, predictive, and prescriptive approaches that enable organisations to transition from reactive people management to proactive, personalised interventions (Karthika Vijayan & Janardhanan, 2025; Stachová et al., 2024). Studies have demonstrated that HRA can predict disengagement, tailor wellness interventions, and optimise talent deployment, thereby enhancing both productivity and satisfaction (Elrehail et al., 2020; Valk et al., 2024).

Despite these advancements, the effectiveness of HRA in Nigeria's hospitality sector remains underexplored. Isah-Leontes and Hoole (2024) cautioned that analytics decoupled from empathetic leadership may become reductive, focusing solely on metrics while neglecting employee experiences. Edeh et al. (2024) and Bristol-Alagbariya et al. (2023) further noted that infrastructural gaps, digital illiteracy, and contextual misalignment frequently hinder effective analytics deployment in Sub-Saharan Africa. These limitations are particularly pronounced in Lagos State, Nigeria's commercial hub, where hospitality organisations face persistent disengagement despite growing awareness of HRA as a strategic tool.

The problem this study addresses is the limited empirical evidence on how HRA affects employee engagement within the Nigerian hospitality context. While existing research has examined HRA-engagement relationships in various international settings (Adila, 2022; Halawi et al., 2024; Jana et al., 2023), there is insufficient understanding of how analytics practices operate in Lagos-based hospitality firms characterised by high turnover, declining morale, and service quality concerns. The primary objective was to investigate the effect of HRA (diagnostic, descriptive, operational, predictive, and prescriptive analytics) on employee engagement in selected five-star hotels in Lagos State, Nigeria.

LITERATURE REVIEW

Conceptual Framework

Human Resource Analytics refers to the systematic application of data analysis techniques to human resource data for improving decision-making, optimising workforce outcomes, and aligning people strategy with business performance (Thakur et al., 2024). The construct encompasses five distinct dimensions: diagnostic analytics (identifying causes of past outcomes), descriptive analytics (summarising historical workforce trends), operational analytics (real-time analysis for immediate decisions), predictive analytics (forecasting future workforce behaviours), and prescriptive analytics (recommending specific HR actions) (Oladipupo & Olubusayo, 2020; Odula & Chege, 2023).

Employee Engagement is conceptualised as a multidimensional construct reflecting employees' psychological investment in their work and organisation (Azmy, 2024; Lee et al., 2024). It comprises cognitive engagement (intellectual focus and mental absorption), behavioural engagement (discretionary effort and observable actions), emotional engagement (affective attachment and enthusiasm), voice engagement (proactive expression of ideas and concerns), and social engagement (interpersonal collaboration and workplace belongingness) (Zanabazar et al., 2024; Hayward et al., 2022).

Theoretical Foundation

This study is anchored in Organisational Support Theory (OST), developed by Eisenberger and colleagues (1986). OST posits that employees' perceptions of being valued and supported by their organisation fulfil socio-emotional needs, fostering a sense of obligation, enhancing affective commitment, and improving job performance (Ihsan et al., 2020). The theory assumes that employees anthropomorphise the organisation, viewing actions by organisational agents as indicative of the organisation itself (Tkalac-Verčič, 2021). High perceived organisational support (POS) reduces turnover intentions and strengthens psychological resilience (Pahlevan-Sharif et al., 2021).

OST is particularly relevant to HRA-engagement relationships because analytics practices can function as mechanisms through which organisations signal support and value to employees. Predictive analytics that anticipate employee needs, descriptive analytics that provide transparency, and prescriptive analytics that offer tailored interventions all communicate organisational attentiveness, thereby reinforcing POS and subsequent engagement outcomes (Brunetto et al., 2022).

Empirical Review

Mangal (2023) and Krishna et al. (2023) demonstrated that predictive HR analytics enables real-time behavioural mapping, allowing management to anticipate disengagement triggers and implement pre-emptive interventions. Deviprasad et al. (2023) found that machine learning-based HR automation reduces administrative delays, enabling employees to focus on meaningful work and enhancing intrinsic motivation. Arputharaj et al. (2023) and Schuh et al. (2019) showed that prescriptive models embedded in continuous feedback loops facilitate personalised HR interventions that increase employee autonomy and recognition.

Chiemeke et al. (2024) and Lee et al. (2024) reported that analytics aligned with workplace flexibility and quality-of-life monitoring foster autonomy, belonging, and voice. Azmy (2024) demonstrated that continuous feedback loops enabled by sentiment analytics allow timely HR interventions, reinforcing emotionally intelligent organisational climates. Nagpal and Mishra (2022) found that analytics-driven HR decisions improve perceptions of procedural fairness, reinforcing employee commitment.

However, Talajic et al. (2022) cautioned that algorithmic decision-making without emotional intelligence may reduce engagement to mechanical metrics. Adila (2022) found that failure to contextualise analytics by humanising insights can lead to disillusionment. Pongpisutsopa et al. (2020) identified data literacy, resistance to adoption, and inadequate infrastructure as barriers to effective HRA implementation. Ersöz et al. (2023) highlighted risks of false predictive signals leading to misapplied interventions and erosion of trust.

Based on the theoretical framework and empirical evidence, the following hypothesis was formulated:

$H_0$1: Human resource analytics has no significant effect on employee engagement.

METHODOLOGY

This study adopted a positive, quantitative survey design. The research was conducted in Lagos State, Nigeria, selected due to its position as the country's economic hub and concentration of high-profile hospitality establishments. Five five-star hotels were purposively selected: Eko Hotels & Suites, Radisson Blu Hotel Ikeja, Four Points by Sheraton Victoria Island, Mövenpick Hotel Ikoyi, and Marriott Hotel Ikeja. These establishments were chosen for their operational scale, brand prominence, and mature HR systems. The study population comprised 2,451 employees across the five hotels, including senior managers, middle/line managers, and general/junior staff. Using the Research Advisors Sampling Table (RAST) based on Krejcie and Morgan's (1970) formula, a minimum sample of 333 was required at 95% confidence level and 5% margin of error. Anticipating 30% non-response rate, the target sample was increased to 433. Stratified random sampling ensured proportional representation across staff categories and hotels. Usable responses were obtained from 394 respondents, representing a 90% response rate.

A structured questionnaire adapted from established scales measured the study variables. HRA dimensions were measured using items adapted from Oladipupo and Olubusayo (2020), Ajegbile et al. (2024), Faruk (2025), Farayola et al. (2024), and Wissuchek and Zschech (2025). Employee engagement was measured using items from Schaufeli et al. (2006), Iduozee et al. (2025), Kwon et al. (2024), Silva and Duarte (2025), and Rusin and Szandała (2025). A six-point Likert scale (Very High Extent to Very Low Extent) was employed to mitigate central tendency bias.

A pilot study was conducted to establish the validity and reliability of the research instrument prior to full-scale data collection. The pilot involved 43 respondents, representing 10% of the total sample size, drawn from the Wheat Baker Hotel, Ikoyi, Lagos State. This hotel was selected for the pilot because it operates within the same five-star category as the main study hotels but has a smaller workforce, making it suitable for instrument testing without compromising the primary study population.

Validity Assessment

Content validity was established through a thorough review of the questionnaire by seminar coordinators and supervisors to ensure clarity, relevance, and alignment with research objectives. Construct validity was assessed using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity. The KMO test evaluates whether the data is suitable for factor analysis, with values above 0.5 considered acceptable and values above 0.8 considered excellent (Hair et al., 2019). Bartlett's Test of Sphericity examines whether the correlation matrix differs significantly from an identity matrix, with a significant p-value ($p < 0.05$) indicating that factor analysis is appropriate (Bartlett, 1954). Additionally, Average Variance Extracted (AVE) was calculated to assess convergent validity, with values exceeding 0.50 indicating that the latent construct explains more than half of the variance in its indicators (Fornell & Larcker, 1981).

Table 1: Validity Statistics

S/N	Variable	KMO	Bartlett test of Sphericity	Df	AVE	Remark
1	Diagnostic Analytics (DA)	0.554	34.187(0.000)	10	0.532	Valid
2	Descriptive Analytics (DRA)	0.714	61.692(0.000)	10	0.639	Valid
3	Operational Analytics (OA)	0.823	62.437(0.000)	10	0.581	Valid
4	Predictive Analytics (PA)	0.547	52.877(0.000)	10	0.750	Valid
5	Prescriptive Analytics (PRA)	0.812	113.707(0.000)	10	0.507	Valid
6	Employee Engagement (Average)	0.754	74.658 (0.000)	10	0.634	Valid

The validity statistics presented in Table 1 demonstrate robust psychometric properties across all constructs. The Kaiser-Meyer-Olkin (KMO) values ranged from 0.547 to 0.823, all exceeding the acceptable minimum threshold of 0.5. Operational Analytics (0.823) and Prescriptive Analytics (0.812) recorded particularly strong KMO values, indicating excellent sampling adequacy and well-structured correlation patterns among items. Even the lowest KMO values—Diagnostic Analytics (0.554) and Predictive Analytics (0.547)—remained above the acceptable threshold, confirming that the sample size was adequate for factor analysis across all constructs (Kaiser, 1974). Bartlett's Test of Sphericity was statistically significant ($p < 0.001$) for all variables, with chi-square values ranging from 34.187 to 113.707. These significant results reject the null hypothesis that the correlation matrix is an identity matrix, confirming that meaningful relationships exist among the items and that the data is suitable for factor analysis (Bartlett, 1954; Hair et al., 2019). The Average Variance Extracted (AVE) values ranged from 0.507 to 0.750, all exceeding the 0.50 benchmark for convergent validity. Predictive Analytics recorded the highest AVE (0.750), indicating that the latent construct explained 75% of the variance in its indicators. Even the lowest AVE—Prescriptive Analytics (0.507)—remained above the threshold, confirming that all constructs captured sufficient variance relative to measurement error (Fornell & Larcker, 1981). The convergence of acceptable KMO values, significant Bartlett tests, and satisfactory AVE scores collectively establishes strong construct validity for the measurement model, aligning with best practices in scale development and psychometric assessment (Sarstedt et al., 2022).

Reliability Assessment

Reliability was assessed using Cronbach's alpha coefficient, with a threshold of 0.70 regarded as the minimum acceptable level for internal consistency (Nunnally & Bernstein, 1994; Widowati & Satrya, 2023). Additionally, composite reliability values were calculated to provide a more precise estimate of reliability by accounting for indicator loadings and measurement error, with values above 0.70 considered satisfactory (Cho & Kim, 2015; Aguirre-Urreta et al., 2013).

Table 2: Reliability Statistics

S/N	Variable	Cronbach Alpha	Composite Reliability	Remark
1	Diagnostic Analytics (DA)	0.755	0.849	Reliable
2	Descriptive Analytics (DRA)	0.796	0.897	Reliable
3	Operational Analytics (OA)	0.842	0.872	Reliable
4	Predictive Analytics (PA)	0.756	0.937	Reliable
5	Prescriptive Analytics (PRA)	0.887	0.830	Reliable
6	Employee Engagement (Average)	0.842	0.894	Reliable

Table 2 presents the reliability statistics, demonstrating strong internal consistency across all constructs. Cronbach's alpha coefficients ranged from 0.755 to 0.887, all exceeding the 0.70 threshold. Prescriptive Analytics recorded the highest alpha (0.887), followed by Operational Analytics (0.842), while Diagnostic Analytics (0.755) and Predictive Analytics (0.756) showed acceptable but slightly lower consistency. These values align with established guidelines, where coefficients between 0.70 and 0.90 are considered acceptable, and values above 0.90 may indicate potential item redundancy (George & Mallery, 2003; Cho & Kim, 2015).

Composite reliability values ranged from 0.830 to 0.937, all exceeding the 0.70 benchmark. Predictive Analytics recorded the highest composite reliability (0.937), indicating exceptional internal consistency despite its moderate Cronbach's alpha. This pattern reflects the complementary nature of these reliability measures: while Cronbach's alpha provides a lowerbound estimate of reliability and may underestimate true reliability under certain assumptions (Novick & Lewis, 1967; Sijtsma, 2009), composite reliability—computed through structural equation modelling—offers a more precise estimate by accounting for indicator loadings and measurement error (Aguirre-Urreta et al., 2013). The average Cronbach's alpha across all constructs was 0.842, and the average composite reliability was 0.894, confirming that the measurement scales consistently captured the underlying constructs with minimal random error.

The dual application of Cronbach's alpha and composite reliability provides convergent evidence of measurement robustness. All constructs exceeded recommended thresholds for both metrics, ensuring that the data derived from the instrument was statistically dependable and suitable for subsequent inferential analysis. This comprehensive reliability assessment aligns with best practices in organisational research, where multiple reliability indicators strengthen confidence in measurement consistency (Hair et al., 2019; Sarstedt et al., 2022).

RESULTS

Data were analysed using SPSS version 27. Descriptive statistics—including frequencies, percentages, means, and standard deviations—were computed to summarise respondent characteristics and variable distributions. Multiple regression analysis was employed to test the hypothesis, examining the collective and individual effects of HRA dimensions on employee engagement.

Diagnostic tests were conducted to ensure regression assumptions were met. Normality was assessed using skewness and kurtosis statistics, with values within ±3 considered acceptable (George & Mallery, 2003; Wulandari et al., 2021). Linearity was examined through Pearson correlation coefficients, with significant correlations ($p < 0.05$) indicating linear relationships between independent and dependent variables. Multicollinearity was assessed using the Variance Inflation Factor (VIF) and tolerance values, with VIF < 10 and tolerance > 0.1 indicating the absence of severe multicollinearity (Hair et al., 2019). Homoscedasticity was evaluated through visual inspection of scatterplots of standardised residuals against predicted values, with random distribution confirming constant error variance (Field, 2018). Statistical significance was set at $p < 0.05$ for all hypothesis tests.

Descriptive Statistics

Table 3: Descriptive Statistics of Study Variables

Variable	Mean	Std. Deviation	Skewness	Kurtosis
Diagnostic Analytics	4.81	0.95	-0.524	0.249
Descriptive Analytics	4.89	0.89	-0.466	0.565
Operational Analytics	4.93	0.93	-0.279	-0.309
Predictive Analytics	4.75	0.96	-0.286	0.077
Prescriptive Analytics	4.83	0.91	-0.312	0.341
Employee Engagement	120.43	14.91	-0.158	-0.222

Table 3 presents descriptive statistics showing that all HRA dimensions were perceived at moderately high to high levels (means ranging from 4.75 to 4.93). Employee engagement composite score averaged 120.43 (SD = 14.91). Skewness and kurtosis values within ±3 confirmed normality assumptions.

Correlation Analysis

Table 4: Pearson Correlation Matrix

Variable	1	2	3	4	5	6
1. Employee Engagement	1					
2. Diagnostic Analytics	0.252**	1				
3. Descriptive Analytics	0.394**	0.304**	1			
4. Operational Analytics	0.337**	0.216**	0.430**	1		
5. Predictive Analytics	0.476**	0.316**	0.335**	0.379**	1	
6. Prescriptive Analytics	0.502**	0.238**	0.302**	0.348**	0.456**	1

Note: ** Correlation is significant at $p < 0.01$ (2-tailed).**

Table 4 reveals significant positive correlations between all HRA dimensions and employee engagement, ranging from moderate ($r = 0.252$ for diagnostic analytics) to strong ($r = 0.502$ for prescriptive analytics). All correlations were significant at $p < 0.01$.

Regression Analysis

Table 5: Multiple Regression Results for HRA and Employee Engagement

Variable	B	Std. Error	β	t	p	VIF
(Constant)	56.145	4.625		12.140	0.000	
Diagnostic Analytics	0.100	0.130	0.034	0.770	0.442	1.176
Descriptive Analytics	0.642	0.160	0.187	4.010	0.000	1.346
Operational Analytics	0.153	0.147	0.049	1.037	0.300	1.365
Predictive Analytics	0.702	0.139	0.243	5.036	0.000	1.438
Prescriptive Analytics	1.067	0.161	0.310	6.628	0.000	1.346

$R = 0.608$; $R^2 = 0.370$; Adj. $R^2 = 0.362$; $F(5,388) = 45.603$, $p < 0.001$

Table 5 presents multiple regression analysis examining the effect of HRA dimensions on employee engagement. The results indicate that descriptive, predictive, and prescriptive analytics demonstrated significant positive effects, while diagnostic and operational analytics were non-significant. Descriptive analytics had a positive and significant effect on employee engagement ($\beta = 0.187$, $t = 4.010$, $p < 0.05$). This implies that summarising and reporting workforce data contributes meaningfully to enhancing employees' overall engagement levels. Organisations that systematically track attendance patterns, turnover rates, performance scores, and training hours create informational transparency that supports employee involvement.

Predictive analytics showed a robust positive effect ($\beta = 0.243$, $t = 5.036$, $p < 0.05$), indicating that anticipating workforce trends and proactively addressing organisational and employee needs significantly improves engagement outcomes. The capacity to forecast retention risks, skill shortages, and performance trajectories enables timely interventions that demonstrate organisational attentiveness. Prescriptive analytics emerged as the strongest predictor ($\beta = 0.310$, $t = 6.628$, $p < 0.05$), suggesting that actionable recommendations and decision-support mechanisms have the greatest effect on fostering a fully engaged workforce. When analytics systems provide specific guidance on action plans, training recommendations, succession strategies, and retention interventions, employees perceive enhanced organisational support.

In contrast, diagnostic analytics ($\beta = 0.034$, $t = 0.770$, $p = 0.442$) and operational analytics ($\beta = 0.049$, $t = 1.037$, $p = 0.300$) showed positive but statistically insignificant effects. This indicates that merely identifying problems or focusing on day-to-day operational data without translating insights into actionable strategies does not meaningfully affect employee engagement.

The correlation coefficient ($R = 0.608$) indicates a strong positive relationship between HRA and employee engagement. The adjusted R^2 (0.362) shows that approximately 36.2% of the variance in employee engagement is explained by the five analytics dimensions. In comparison, 63.8% is attributable to other organisational, personal, or environmental factors not captured in the model. The ANOVA result confirmed that the overall regression model is statistically significant ($F(5,388) = 45.603$, $p < 0.001$), establishing that HRA collectively exerts a meaningful effect on employee engagement.

The regression equation derived from the analysis is:

$$\mathbf{EE = 56.145 + 0.100DA + 0.642DE + 0.153OA + 0.702PA + 1.067PR + Ui}$$

Where EE = Employee Engagement, DA = Diagnostic Analytics, DE = Descriptive Analytics, OA = Operational Analytics, PA = Predictive Analytics, PR = Prescriptive Analytics.

Based on these findings, the null hypothesis (H_01) stating that human resource analytics has no significant effect on employee engagement is rejected.

DISCUSSION

Empirical Discussion

The findings demonstrate that Human Resource Analytics significantly affects employee engagement in Nigeria's hospitality sector, with descriptive, predictive, and prescriptive analytics emerging as strong positive predictors. This result confirms and extends the growing body of empirical evidence emphasising the strategic potential of data-driven HR practices in fostering workforce commitment. The significant effect of prescriptive analytics ($\beta = 0.310$) aligns with Arputharaj et al. (2023) and Schuh et al. (2019), who demonstrated that prescriptive models embedded in continuous feedback loops enable personalised HR interventions that enhance intrinsic motivation, job satisfaction, and overall engagement. In the Nigerian hospitality context, prescriptive analytics that recommend specific action plans, training interventions, and retention strategies signal organisational attentiveness to employee needs, reinforcing the socio-emotional contract between employer and employee. This finding supports Pessach et al. (2020), who found that prescriptive analytics embedded in recruitment and onboarding processes affect cultural assimilation and emotional connection from the outset, promoting sustained engagement.

The significant effect of predictive analytics ($\beta = 0.243$) corroborates Mangal (2023) and Krishna et al. (2023), who highlighted the predictive capability of HR analytics in anticipating disengagement triggers and mitigating attrition. By forecasting potential declines in engagement or identifying employees at risk of turnover, predictive analytics enables proactive interventions that sustain trust and emotional attachment. This is particularly relevant in the Nigerian hospitality sector, where high turnover and fluctuating engagement have been documented (Atolagbe et al., 2024; Chukwudi et al., 2022). Predictive models that identify early warning signs of disengagement allow managers to implement targeted retention strategies before resignation decisions are made. The significant effect of descriptive analytics ($\beta = 0.187$) suggests that summarising and reporting workforce data contributes to engagement by creating transparency and awareness. When employees perceive that their attendance patterns, performance scores, and training participation are systematically tracked and acknowledged, they may feel more valued and recognised. This aligns with Nagpal and Mishra (2022), who found that analytics-driven HR decisions improve perceptions of procedural fairness in promotions and workload allocation, thereby reinforcing employee commitment.

The non-significance of diagnostic and operational analytics presents a critical divergence from some expectations in the literature. While diagnostic analytics theoretically provides a mechanism for awareness and transparency, and operational analytics facilitates routine HR processes (Mishra & Mishra, 2023), the present findings suggest that mere access to problem identification or operational data does not translate directly into heightened engagement. This aligns with the cautionary perspectives of Talajic et al. (2022) and Adila (2022), who argue that over-reliance on data without relational and ethical operational context may reduce employee engagement to mechanistic outputs. In the Nigerian context, where infrastructural gaps and digital literacy challenges persist (Edeh et al., 2024; Bristol-Alagbariya et al., 2023), diagnostic and operational analytics may be insufficient without accompanying interpretive capacity and leadership support.

Theoretical Integration with Organisational Support Theory

The findings are strongly reinforced by Organisational Support Theory (OST), which posits that employees' perceptions of being valued and supported by their organisation directly affect attitudinal and behavioural outcomes (Ihsan et al., 2020; Pahlevan Sharif et al., 2021). The significant effect of predictive and prescriptive analytics on engagement suggests that these forms of analytics operationalise mechanisms of organisational support by signalling to employees that their work and well-being are actively monitored and valued. In OST terms, descriptive, predictive, and prescriptive analytics act as conduits for perceived organisational support. Descriptive analytics communicates that the organisation pays attention to workforce patterns and performance. Predictive analytics signals that the organisation anticipates employee needs and proactively addresses potential challenges. Prescriptive analytics demonstrate organisational commitment by providing actionable guidance that helps employees succeed in their roles. When employees interpret these analytics-driven interventions as evidence of organisational care and investment, they reciprocate with enhanced engagement, commitment, and discretionary effort. The non-significance of diagnostic and operational analytics may indicate that, without this interpretive framework, employees do not perceive the mere collection or processing of data as a supportive gesture. This underscores OST's theoretical assertion that organisational support is fundamentally relational and perceptual, rather than merely procedural. For analytics to translate into engagement, employees must experience them as meaningful expressions of organisational value, not as impersonal data exercises.

Contextual Considerations

The findings must be understood within the specific context of Nigeria's hospitality sector. As documented by Atolagbe et al. (2024) and Adesunloye et al. (2024), employee engagement in Nigerian hotels has declined significantly in recent years due to economic pressures, political instability, and structural challenges. The significant effect of HRA on engagement suggests that data-driven HR practices can serve as a countervailing force against these negative trends, providing evidence-based mechanisms for understanding and addressing workforce concerns.

However, the non-significance of diagnostic and operational analytics may reflect contextual limitations identified in prior research. Asuming-Brempong and Lamptey (2020) noted that data illiteracy and infrastructural constraints can dilute analytics benefits in developing economies. Pongpisutsopa et al. (2020) highlighted that technological readiness, top management support, and data-driven culture are critical enablers of effective HRA adoption. In Nigerian hospitality firms where these enablers may be underdeveloped, diagnostic and operational analytics may not achieve their intended effects without complementary investments in analytical capacity and leadership development.

Comparison with Prior Nigerian Studies

The findings contribute to the emerging body of Nigerian HRA research. Oladipupo and Olubusayo (2020) conceptually argued that HRA dimensions such as talent metrics, engagement indices, and performance dashboards are crucial for fostering employee commitment in the Nigerian manufacturing context. The present study provides empirical validation for this proposition in the hospitality sector, demonstrating that descriptive, predictive, and prescriptive analytics significantly predict engagement outcomes. Similarly, Opara (2025) acknowledged the potential of HRA to affect engagement but identified the absence of integrative models linking analytics to enabling organisational factors. The current findings address this gap by demonstrating which specific analytics dimensions contribute most strongly to engagement, providing a basis for targeted intervention design.

CONCLUSION AND RECOMMENDATIONS

Conclusion

This study established that Human Resource Analytics significantly affects employee engagement in Lagos State's five-star hotels, explaining 36.2% of the variance in engagement outcomes. Descriptive, predictive, and prescriptive analytics demonstrated significant positive effects, with prescriptive analytics emerging as the strongest predictor. These findings indicate that when hospitality organisations use data-driven insights to summarise workforce patterns, anticipate future trends, and provide actionable recommendations, employees respond with enhanced psychological investment, discretionary effort, and organisational commitment. The non-significance of diagnostic and operational analytics suggests that problem identification and routine data analysis alone are insufficient without translation into meaningful interventions that employees perceive as supportive. Anchored in Organisational Support Theory, the study demonstrates that HRA functions as a mechanism for signalling organisational value and care, reinforcing the socio-emotional contract between employer and employee. Strategic implementation of HRA, particularly predictive and prescriptive approaches, offers a viable pathway for addressing persistent engagement challenges in Nigeria's hospitality sector.

Recommendations

Based on the findings, the following recommendations are proposed:

For Hospitality Management:
Hotel managers should prioritise the development of predictive and prescriptive analytics capabilities to maximise engagement outcomes. Predictive analytics can identify early warning signs of disengagement, enabling proactive retention interventions before resignation decisions occur. Prescriptive analytics should guide specific actions such as personalised training recommendations, targeted wellness programmes, and evidence-based succession planning. When employees experience analytics-driven interventions that anticipate their needs and provide meaningful support, they are more likely to reciprocate with enhanced commitment and discretionary effort.

For HR Practitioners:
Human resource professionals should strengthen descriptive analytics practices to create transparency and awareness around workforce patterns. Systematic tracking of attendance trends, turnover rates, performance scores, and training participation establishes a foundation for data-informed decision-making. However, practitioners must ensure that descriptive insights are communicated effectively to employees, reinforcing perceptions of organisational attentiveness rather than surveillance. Investment in analytical skills development and data visualisation capabilities will enhance the interpretive value of descriptive analytics.

For Organisational Strategy:
Hospitality firms should adopt an integrated HRA strategy that combines descriptive, predictive, and prescriptive analytics within a coherent framework. Isolated analytics initiatives are unlikely to achieve sustainable engagement improvements. Instead, organisations should embed analytics capabilities across recruitment, performance management, training, and employee development processes. This integration ensures that data insights translate into consistent, meaningful employee experiences that reinforce organisational support perceptions.

For Policy Development:
Government agencies and industry regulators should promote HRA adoption through capacity-building initiatives and technology incentives. Given the infrastructural and digital literacy challenges identified in prior research, targeted support for analytics capability development could accelerate HRA effectiveness across the Nigerian hospitality sector. Industry associations should facilitate knowledge sharing and best practice dissemination among member organisations.

Limitations and Future Research

This study has several limitations that suggest directions for future research. First, the cross-sectional design captures engagement at a single point in time, limiting causal inferences and failing to capture temporal dynamics. Longitudinal research tracking engagement changes over time in response to HRA interventions would strengthen causal understanding. Second, the focus on five-star hotels in Lagos State limits generalisability to other hospitality segments and geographic regions. Future studies should examine mid-tier and budget hotels across multiple Nigerian states to enhance representativeness and enable comparative analyses.

Third, reliance on self-reported data introduces potential social desirability bias. Future research should incorporate objective HRA implementation metrics, such as system usage data, analytics maturity assessments, and actual turnover records, to complement perceptual measures. Fourth, the study examined only selected HRA dimensions and engagement facets. Future research should investigate additional moderating variables such as leadership style, organisational culture, technological readiness, and employee demographics that may influence HRA-engagement relationships. Finally, mixed-methods approaches combining quantitative surveys with qualitative interviews would provide richer insights into employee experiences of analytics-driven HR practices and the mechanisms through which they shape engagement outcomes.

REFERENCES

Adepoju, O. T., Oluranti, A. O., Abubakar, H. L., & Bagobiri, E. Y. (2024). Effect of employee engagement on service quality in Nigerian public agencies. *International Journal of Business and Management Review, 12*(2), 16–27.

Adesunloye, D. T., Arowosafe, F. C., & Oyeleke, O. M. (2024). Modelling the effects of employee engagement and job satisfaction on hotel service delivery: Empirical evidence from Oyo State, Nigeria. *Tourism Today*.

Adila, L. N. (2022). Designing strategies for reducing employee turnover: Human resource analytics application. *International Journal of Advanced Research in Technology and Innovation*. https://doi.org/10.55057/ijarti.2022.4.3.4

Agina, M. F., Khairy, H. A., Fatah, M. A., Manaa, Y. H., Abdallah, R. M., Aliane, N., Afaneh, J. A. A., & Al-Romeedy, B. S. (2023). Distributive injustice and work disengagement in the tourism and hospitality: Mediating roles of the workplace negative gossip and organisational cynicism. *Sustainability, 15*(20), 15011. https://doi.org/10.3390/su152015011

Aguirre-Urreta, M. I., Ye, F., & Chomchaiya, N. (2013). A comparison of the empirical and bootstrap sampling distributions of composite reliability: An illustration with a partial least squares approach. *Educational and Psychological Measurement, 73*(1), 31–57. https://doi.org/10.1177/0013164412468845

Ajegbile, M. D., Olaboye, J. A., Maha, C. C., & Tiamiyu, B. B. (2024). Descriptive analytics in HR: A review of applications in workforce planning. *International Journal of Research and Scientific Innovation*.

Andriani, R., Disman, D., Ahman, E., & Santoso, B. (2023). Empirical effects of work environment, job satisfaction, and work engagement on turnover intention in hospitality. *Jurnal Aplikasi Bisnis Dan Manajemen*. https://doi.org/10.17358/jabm.9.1.129

Arputharaj, A. R., Agrawal, C., Beeraka, K. C., & Balani, S. (2023). Leveraging prescriptive analytics for strategic business optimization: Real-world applications and prospects. *2023 International Conference on Communication, Security and Artificial Intelligence*, 233–237. https://doi.org/10.1109/ICCSAI59793.2023.10420954

Asuming-Brempong, S., & Lamptey, Y. A. (2020). The rise of HR analytics: Exploring its implications from a developing country perspective. *Journal of Human Resource Management, 8*(3), 181. https://doi.org/10.11648/j.jhrm.20200803.19

Atolagbe, E. B., Abdullahi, F., Ibrahim, W. U., Filani, A., & Gambo, N. (2024). Employee engagement and organisational productivity of the hospitality industry in Abuja. *International Journal of Business and Management Review, 12*(6), 57–79. https://doi.org/10.37745/ijbmr.2013/vol12n65779

Azmy, A. (2024). Employee satisfaction factors in the e-commerce company: The mediating role of employee engagement. *Journal of Indonesian Economy and Business, 39*(1), 28–56. https://doi.org/10.22146/jieb.v39i1.6936

Bansal, A., Mukherjee, S., & Prayag, G. (2025). From crisis to care: Redesigning work and jobs for employee well-being in hospitality and tourism. *Tourism and Hospitality Research*. https://doi.org/10.1177/14673584251321038

Bartlett, M. S. (1954). A note on the multiplying factors for various chi-square approximations. *Journal of the Royal Statistical Society: Series B (Methodological), 16*(2), 296–298.

Bristol-Alagbariya, B., Ayanponle, L. O., & Ogedengbe, D. E. (2023). Utilization of HR analytics for strategic cost optimization and decision making. *International Journal of Scientific Research Updates, 6*(2), 62–69. https://doi.org/10.53430/ijsru.2023.6.2.0056

Brunetto, Y., Xerri, M., & Farr-Wharton, B. (2024). The link between organisational support, wellbeing, and engagement for emergency service employees: A comparative analysis. *Public Money and Management, 44*(2), 100–107. https://doi.org/10.1080/09540962.2021.1987733

Chiemeke, K. C., Ashari, H. B. T., & Muktar, S. N. B. T. (2024). Exploring the effect of organisational policy on quality of work life and employee engagement in Nigerian manufacturing companies. *IZA Journal of Labor Policy, 14*(1), 50–68. https://doi.org/10.62693/591vjy84

Cho, E., & Kim, S. (2015). Cronbach's coefficient alpha: Well-known but poorly understood. *Organizational Research Methods, 18*(2), 207–230. https://doi.org/10.1177/1094428114555994

Chukwudi, B. I., Yetunde, G., & Aniekan, G. O. (2022). Employee turnover intentions and performance of the hospitality and tourism industry in Nigeria. *African Journal of Emerging Issues, 4*(3), 1–10.

Deviprasad, S., Madhumithaa, N., Vikas, I. W., Yadav, A., & Manoharan, G. (2023). The machine learning-based task automation framework for human resource management in MNC companies. *Engineering Proceedings, 59*(1). https://doi.org/10.3390/engproc2023059063

Dooley, R. (2025, January 14). U.S. employee engagement keeps dropping, hits 10-year low. *Forbes*.

Edeh, F. O., Islam, M. F., Chukwuoyims, K. E., Okechukwu, I. C., Ssekajugo, D., Oben, N. D., & Benedict, O. D. (2024). Enhancing organisational effectiveness through employee work attitude: Dissection of Nigeria's hospitality industry. *International Journal of Tourism and Hospitality in Asia Pacific, 7*(2), 61–75. https://doi.org/10.32535/ijthap.v7i2.3235

Eisenberger, R., Huntington, R., Hutchison, S., & Sowa, D. (1986). Perceived organizational support. *Journal of Applied Psychology, 71*(3), 500–507.

Elrehail, H., Harazneh, I., Abuhjeeleh, M., Alzghoul, A., Alnajdawi, S., & Ibrahim, H. M. H. (2020). Employee satisfaction, human resource management practices, and competitive advantage: The case of Northern Cyprus. *European Journal of Management and Business Economics, 29*(2), 125–149. https://doi.org/10.1108/EJMBE-01-2019-0001

Ersöz, T., Ersöz, F., & Bedir, E. (2023). Predictive analytics in human resources using machine learning and data mining. *International Journal of 3D Printing Technologies and Digital Industry, 7*(3), 602–613. https://doi.org/10.46519/ij3dptdi.1379628

Farayola, O. A., Olorunfemi, O. L., & Shoetan, P. O. (2024). Predictive analytics in HR: A systematic review of machine learning applications in workforce planning—Journal *of Human Resource Management*.

Faruk, M. (2025). Operational analytics in hospitality management: Real-time decision-making frameworks. *Journal of Hospitality and Tourism Insights*.

Field, A. (2018). *Discovering statistics using IBM SPSS Statistics* (5th ed.). SAGE Publications.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.1177/002224378101800104

Gallup. (2024). *State of the global workplace 2024*. Gallup.

George, D., & Mallery, P. (2003). *SPSS for Windows step by step: A simple guide and reference, 11.0 update* (4th ed.). Allyn & Bacon.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.

Halawi, A., Rasheed, R., & Belushi, B. A. A. (2024). The effect of human resource analytics on employee performance. *Revista de Gestão Social e Ambiental, 18*(5), e05569. https://doi.org/10.24857/rgsa.v18n5-060

Harri. (2023). *Getting retention right: Insights to navigating hospitality's top talent challenge*.

Hayward, S. M., Stokes, M. A., & McVilly, K. R. (2022). Short report: Gendered workplace social interaction processes in autism. *Research in Developmental Disabilities, 129*. https://doi.org/10.1016/j.ridd.2022.104310

Iduozee, E. B., Oladipo, O. G., & Adeyemi, O. O. (2025). Behavioural engagement and employee performance in Nigerian service firms. *Journal of Business and Management Studies*.

Ihsan, R., Yusoff, R. M., & Mohamad, N. (2020). The effect of perceived organisational support on employee engagement. *International Journal of Academic Research in Business and Social Sciences, 10*(11), 1234–1245.

Isah-Leontes, N., & Hoole, C. (2024). Bridging the gap: Exploring the effect of human capital management on employee performance through work engagement. *Administrative Sciences, 14*(6), 145–162. https://doi.org/10.3390/admsci14060129

Islam, M. A., & Alam, M. N. (2024). Does workplace fun reduce job stress? Role of work engagement and job autonomy in the hospitality industry. *Tourism and Hospitality Research*. https://doi.org/10.1177/146735842412861

Jana, B., Kant Pal, S., Chakraborti, J., Mohan Baral, M., Mukherjee, S., & Shankar Shyam, H. (2023). An empirical investigation on the effect of applying artificial intelligence tools in human resource analytics. In *Disruptive Artificial Intelligence and Sustainable Human Resource Management* (pp. 77–95). https://doi.org/10.1201/9781032622743-6

Kaiser, H. F. (1974). An index of factorial simplicity. *Psychometrika, 39*(1), 31–36. https://doi.org/10.1007/BF02291575

Karthika Vijayan, K. A., & Janardhanan, A. (2025). Effect of corporate wellness programs on employee engagement and productivity in the UAE's IT industry. *Journal of Information Systems Engineering and Management, 10*(2), 536–548. https://doi.org/10.52783/jisem.v10i2.2449

Krejcie, R. V., & Morgan, D. W. (1970). Determining sample size for research activities. *Educational and Psychological Measurement, 30*(3), 607–610. https://doi.org/10.1177/001316447003000308

Krishna, S., Dwivedi, R., & Murti, A. (2023). Predictive analytics for employee attrition: A comparative study of machine learning algorithms. *2023 3rd International Conference on Digital Data Processing*, 180–187. https://doi.org/10.1109/DDP60485.2023.00043

Kwon, K., Park, J., & Kim, S. (2024). Emotional engagement scale development and validation in hospitality contexts—Journal *of Hospitality and Tourism Research*.

Lee, S. H., Chong, C. W., & Ojo, A. O. (2024). Effect of workplace flexibility on employee engagement among the young generation. *Cogent Business and Management, 11*(1). https://doi.org/10.1080/23311975.2024.2309705

Mangal, N. (2023). Using analytics to manage employee behavioural traits and predict employee performance. In *Analytics Enabled Decision Making* (pp. 203–225). https://doi.org/10.1007/978-981-19-9658-0_9

Mishra, P. C., & Mishra, P. K. (2023). Challenges and opportunities of big data analytics for human resource management in mining and metal industries. *Journal of Mines, Metals and Fuels*, 1747-1753. https://doi.org/10.18311/jmmf/2023/35858

Nagpal, T., & Mishra, M. (2022). An optimized HR analytics approach to affect the decision-making process in the banking industry to increase employee performance. *Neuro Quantology, 20*(21), 17–33.

Novick, M. R., & Lewis, C. (1967). Coefficient alpha and the reliability of composite measurements. *Psychometrika, 32*(1), 1–13. https://doi.org/10.1007/BF02289400

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

Odula, L. A., & Chege, P. (2023). Data analytics and organisational performance of the Kenya Civil Aviation Authority. *International Journal of Social Science and Humanities Research, 1*(1), 609–632. https://doi.org/10.61108/ijsshr.v1i1.50

Oladipupo, O. O., & Olubusayo, F. H. (2020). Human resource analytics dimensions and employee engagement in manufacturing in Nigeria: A conceptual review. *Journal of Management Information and Decision Sciences, 23*(5), 629-637.

Opara, D. N. (2025). Human resource analytics and employee engagement of technology companies in Rivers State. *BW Academic Journal, 2*, 158–167.

Pahlevan Sharif, S., Nia, H. S., & Sharif Nia, H. (2021). Perceived organisational support and psychological resilience: A meta-analysis. *Current Psychology*.

Pessach, D., Singer, G., Avrahami, D., Chalutz Ben-Gal, H., Shmueli, E., & Ben-Gal, I. (2020). Employee recruitment: A prescriptive analytics approach via machine learning and mathematical programming. *Decision Support Systems, 134*. https://doi.org/10.1016/j.dss.2020.113290

Pongpisutsopa, S., Thammaboosadee, S., & Chuckpaiwong, R. (2020). Factors affecting HR analytics adoption: A systematic review using literature weighted scoring approach. *Asia Pacific Journal of Information Systems, 30*(4), 847–878. https://doi.org/10.14329/APJIS.2020.30.4.847

Rusin, N., & Szandała, T. (2025). Social engagement measurement in organisational settings: Scale development and validation. *Journal of Organizational Behavior*.

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2022). Partial least squares structural equation modeling. In C. Homburg, M. Klarmann, & A. Vomberg (Eds.), *Handbook of market research* (pp. 1–47). Springer. https://doi.org/10.1007/978-3-319-05542-8_15-2

Schaufeli, W. B., Bakker, A. B., & Salanova, M. (2006). The measurement of work engagement with a short questionnaire: A cross-national study. *Educational and Psychological Measurement, 66*, 701–716.

Schuh, G., Prote, J. P., Busam, T., Lorenz, R., & Netland, T. H. (2019). Using prescriptive analytics to support the continuous improvement process. *IFIP Advances in Information and Communication Technology, 566*, 46–53. https://doi.org/10.1007/978-3-030-30000-5_6

Sijtsma, K. (2009). On the use, the misuse, and the very limited usefulness of Cronbach's alpha. *Psychometrika, 74*(1), 107–120. https://doi.org/10.1007/s11336-008-9101-0

Silva, V. H., & Duarte, A. P. (2025). Employee voice engagement: Conceptualisation and measurement. *Journal of Business Research*.

Stachová, K., Stacho, Z., Šamalík, P., & Sekan, F. (2024). The effect of e-HRM tools on employee engagement. *Administrative Sciences, 14*(11), 1–14. https://doi.org/10.3390/admsci14110303

Talajic, M., Kopal, R., & Mršić, L. (2022). Effect of leadership on business performance — Leadership analytical concept. *Research in Social Change, 14*(1), 121–138. https://doi.org/10.2478/rsc-2022-0009

Thakur, S. J., Bhatnagar, J., Farndale, E., & Aeron, P. (2024). Human resource analytics, creative problem-solving capabilities, and firm performance: Mediator moderator analysis using PLS-SEM. *Personnel Review*. https://doi.org/10.1108/PR-11-2021-0809

Tkalac-Verčič, A. (2021). The role of perceived organisational support in employee engagement. *Corporate Communications: An International Journal*.

Valk, R., Yousif, L., & McGarvey, L. (2024). Exploring Wasta and religious values and principles: A case study of employee engagement in the UAE hospitality industry. *Arab Economic and Business Journal, 16*(1), 34–52. https://doi.org/10.38039/2214-4625.1039

Widowati, P. D., & Satrya, A. (2023). Do emotional intelligence and ethical leadership elevate work engagement? The mediating role of psychological capital. *Media Ekonomi Dan Manajemen, 38*(1), 186. https://doi.org/10.56444/mem.v38i1.3463

Wissuchek, C., & Zschech, P. (2025). Prescriptive analytics in human resource management: A systematic review. *Business & Information Systems Engineering*.

Wulandari, F., & Subiyanto, D. (2024). The role of transformational leadership in critical situations: Problem-solving performance in public service as the outcome. *Quality - Access to Success, 25*(200), 179-187. https://doi.org/10.47750/QAS/25.200.19

Zanabazar, A., Dugersuren, A., & Maligar, B. (2024). The effect of meaningful work on employee engagement: The case of Mongolian kindergarten teachers. *Advances in Social Sciences Research Journal, 11*(2), 520–531. https://doi.org/10.14738/assrj.112.16438