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**HUMAN RESOURCE MANAGEMENT PRACTICES, BIG DATA  
ANALYTICS AND EMPLOYEE PERFORMANCE IN ACCESS  
BANK PLC, ABUJA, NIGERIA**

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**Abstract**

*This study examined whether big data analytics mediates the relationships between human resource management practices and employee performance in Access Bank Plc branches in Abuja, Nigeria. Recruitment and selection, compensation, and training and development were modeled as the human-resource practices, while big data analytics served as the mediator. A quantitative cross-sectional survey was conducted among employees drawn from six Abuja branch locations. From an estimated population of 350 employees, 187 questionnaires were distributed through proportionate stratified random sampling and 172 usable responses were returned, representing a 91.9% response rate. Confirmatory factor analysis supported the five-construct measurement model: standardized loadings ranged from .84 to .94, average variance extracted ranged from .744 to .815, composite reliability ranged from .897 to .930, and Cronbach's alpha ranged from .862 to .903. Pearson correlations and Hayes PROCESS Model 4 with 5,000 bootstrap samples were used for hypothesis testing. Recruitment and selection had a significant indirect effect on performance through big data analytics (effect = .0787, 95% bootstrap CI [.0090, .1768]) but a nonsignificant direct effect, indicating indirect-only mediation. Compensation had no significant indirect effect (effect = -.0300, 95% CI [-.0776, .0015]). Training and development had significant direct and indirect effects (indirect effect = .0552, 95% CI [.0065, .1337]), indicating partial mediation. Big data analytics positively predicted employee performance ( $\beta = .2328$ ,  $p = .0020$ ). The findings show that analytics capability converts selected HR practices—especially recruitment and employee development—into stronger performance, but*

*does not automatically make compensation effective. The study recommends integrating HR and performance data, strengthening data literacy, using analytically informed recruitment, and aligning compensation with transparent performance evidence.*

**Keywords:** human resource management; big data analytics; employee performance; recruitment and selection; compensation; training and development; banking

## Introduction

Banks operate in a data-intensive environment characterized by digital transactions, rapid product innovation, regulatory scrutiny, cybersecurity risk, changing customer expectations, and intense competition. Their performance depends not only on technology and capital but also on employees who interpret information, serve customers, manage risk, and execute strategy. Human resource management (HRM) therefore remains a central mechanism for attracting competent people, motivating contribution, and developing capabilities. However, conventional HR decisions based mainly on intuition or fragmented records may be too slow and imprecise for contemporary banking. Big data analytics offers a means of converting high-volume, high-velocity, and varied organizational data into evidence for decisions. In HRM, analytics can combine recruitment records, competency information, learning histories, compensation data, attendance, engagement, customer outcomes, and performance indicators. The resulting patterns can improve workforce planning, identify skill gaps, evaluate interventions, and support more timely decisions. Analytics is valuable only when information is accurate, relevant, accessible, and connected to managerial action; collecting more data without analytical capability does not itself improve performance.

Recruitment and selection determine the quality and fit of employees entering the organization. Structured assessment, competency profiles, and evidence-based screening can improve person–job and person–organization fit. Compensation influences effort, retention, perceptions of fairness, and the attractiveness of employment. Training and development build knowledge and adaptability, particularly where technology and regulation change quickly. Each practice may affect employee performance directly, but its effect may also depend on the organization's capacity to analyze data and translate it into better decisions.

Access Bank Plc is a major Nigerian financial institution with branches across Abuja. The bank's workforce must deliver efficient service, maintain compliance, adopt digital tools, and respond to changing customer demands. These conditions create a practical need to understand how HR practices and big data analytics work together. Although Nigerian organizations increasingly discuss artificial intelligence and data-driven management, evidence on the mechanism linking HRM practices to employee performance remains limited, especially at branch level.

The problem is that investment in recruitment, compensation, or training does not guarantee improved employee performance. Recruitment data may remain disconnected from later performance, reward systems may not reflect contribution, and training records may measure attendance rather than capability. Big data analytics may explain why some HR practices generate better outcomes than others: it can reveal patterns, personalize interventions, and connect HR decisions with operational results. Yet the mediation pathway has received less attention than simple direct relationships.

This study addresses that gap by assessing the direct and indirect relationships among recruitment and selection, compensation, training and development, big data analytics, and employee performance in Access Bank Plc, Abuja. It asks whether analytics acts as an organizational capability through which HR practices yield performance benefits and whether that role differs across the three practices.

## **Objectives and Hypotheses**

The study sought to determine the effects of recruitment and selection, compensation, and training and development on employee performance and to test whether big data analytics mediates each relationship. The direct-effect null hypotheses stated that each HRM practice has no significant effect on performance. The mediation null hypotheses stated that big data analytics does not significantly mediate the relationship between each practice and employee performance.

## **Significance and Scope**

The study provides managers with evidence on where analytics adds value within the HR system. It helps HR professionals distinguish data collection from analytical capability, directs investment toward practices with supported pathways, and contributes Nigerian banking evidence to the literature on strategic HRM and people analytics. The scope covered employees in six Access Bank branch locations in Abuja and focused on perceptions of the five study constructs at one point in time.

## **Literature Review**

### **2.1 Conceptual Review**

#### **Human resource management practices**

HRM practices are coordinated policies and activities used to acquire, deploy, motivate, develop, and retain employees. Their strategic value lies in internal alignment: staffing identifies capable employees; training develops their competence; compensation signals valued behavior; and performance information supports adjustment. Isolated practices can send conflicting messages, whereas a coherent bundle creates clearer expectations and stronger employee responses (Armstrong & Taylor, 2020). In this study, HRM is represented by recruitment and selection, compensation, and training and development.

#### **Recruitment and selection**

Recruitment attracts a pool of potential employees, while selection evaluates applicants and chooses those most likely to meet job and organizational requirements. Effective systems use valid job analysis, transparent criteria, structured interviews, tests, background information, and consistent decision rules. In banking, selection must consider technical competence, customer orientation, ethical judgment, adaptability, and risk awareness. Poor selection creates costs through weak service, errors, turnover, and additional training.

Analytics can strengthen recruitment by identifying characteristics associated with later performance and retention, monitoring sources of successful hires, detecting bottlenecks, and reducing reliance on unstructured judgment. Nevertheless, models can reproduce historical bias when input data or target outcomes are flawed. Human oversight, explainability, privacy protection, and periodic validation are therefore essential.

#### **Compensation**

Compensation includes direct financial rewards, incentives, benefits, recognition, and other returns employees receive for their contribution. An effective system should be internally equitable, externally competitive, understandable, affordable, and aligned with performance. Expectancy and equity mechanisms suggest that employees exert effort when they believe performance will be recognized and rewards are fair. Compensation can become counterproductive when criteria are opaque, incentives encourage narrow targets, or rewards ignore teamwork and risk.

Data analytics can support benchmarking, pay-equity reviews, incentive modeling, and analysis of relationships among reward, retention, engagement, and performance. However, analytical sophistication cannot correct a poorly designed reward philosophy. A statistically optimized system may still fail if employees distrust the measures or cannot see how rewards connect to controllable performance.

### **Training and development**

Training improves knowledge and skills required for current roles, while development prepares employees for broader and future responsibilities. In banking, continuous learning is needed for digital platforms, cybersecurity, customer service, compliance, credit assessment, and leadership. Training contributes to performance when it addresses a verified need, uses suitable delivery methods, provides opportunities for application, and receives supervisory support.

Analytics can identify skill gaps, recommend learning, monitor participation, compare pre- and post-training outcomes, and connect learning histories with performance. These capabilities make training more targeted and allow resources to be redirected toward programmes with evidence of transfer. Because learning generates longitudinal data, training is especially suited to an analytics-enabled improvement cycle.

### **Big data analytics**

Big data analytics refers to the technologies, skills, governance arrangements, and routines used to process large and diverse datasets and generate descriptive, predictive, or prescriptive insight. In HRM it is often described as people analytics or workforce analytics. Descriptive analysis explains what has happened; predictive analysis estimates likely outcomes; prescriptive analysis recommends actions. Capability depends on data quality, integration, analytical competence, managerial acceptance, and responsible governance.

The construct should not be confused with artificial intelligence alone. AI techniques may form part of an analytics system, but value also comes from sound definitions, reliable databases, basic statistical reasoning, visualization, and disciplined use of evidence. Ethical concerns include privacy, surveillance, algorithmic bias, data security, lack of explanation, and inappropriate automation of consequential employment decisions. Responsible use requires purpose limitation, access control, audit trails, human review, and employee trust.

### **Employee performance**

Employee performance is the extent to which an individual produces behaviors and outcomes that support organizational goals. It includes task performance, service quality, accuracy, adaptability, citizenship behavior, and compliance with rules. In banking, performance must balance commercial outcomes with customer protection and risk control. A narrow focus on sales can encourage harmful behavior; balanced measurement is therefore necessary.

### **Linking HRM, analytics and performance**

The proposed mechanism is that HR practices generate workforce information and shape employee capability and motivation, while analytics improves the quality of decisions made from that information. Recruitment generates applicant and selection data; compensation generates reward and outcome data; training generates need, participation, and learning data. When these data are connected with employee performance, managers can refine criteria, target development, and allocate resources. Analytics therefore acts as a complementary capability rather than an independent substitute for good HRM.

## **2.2 Empirical Review**

Empirical research generally associates strategic HRM bundles with employee and organizational performance, although effect sizes vary by context, implementation quality, and measurement. Studies of recruitment emphasize person–job fit, structured assessment, and technology-enabled screening. Evidence on compensation is more conditional because rewards can motivate performance but also create perceptions of inequity or encourage gaming. Training research more consistently reports positive outcomes when needs assessment, transfer climate, and evaluation are present.

The emerging people-analytics literature suggests that data capability improves workforce planning and enables HR functions to demonstrate business value. Analytics can support evidence-based staffing, predict turnover, identify high-impact learning, and improve talent allocation. However, organizations frequently remain at a descriptive reporting stage. Barriers include fragmented systems, insufficient analytical skill, weak data quality, privacy concerns, and limited managerial sponsorship (Marler & Boudreau, 2017; Tursunbayeva et al., 2018).

Recent studies in developing economies report growing adoption of analytics but also caution that organizational readiness determines results. Technology produces value when combined with human expertise and decision routines. Nigerian evidence has linked HR practices with employee performance and identified increasing interest in big data, yet few studies test analytics as a mediator across distinct HR practices in commercial banking. This study responds by comparing three indirect pathways within one model.

The empirical gap is threefold. First, much prior work estimates only direct HRM–performance relationships. Second, studies often combine practices into a single index, concealing differences among staffing, reward, and development. Third, evidence from Nigerian banking and Abuja branches is limited. Testing bootstrapped indirect effects provides a stronger assessment of the proposed mechanism than relying only on separate significant regressions.

## 2.3 Theoretical Review

### Resource-based view

The resource-based view (RBV) explains sustained performance through valuable, rare, difficult-to-imitate, and organizationally embedded resources (Barney, 1991). Employee knowledge and relationships can satisfy these conditions when supported by coherent HR systems. Recruitment acquires human capital, training develops it, and compensation helps motivate and retain it. The theory is relevant because competitors may imitate a single practice more easily than an integrated combination of talent, data, routines, and managerial judgment.

Big data analytics can be understood as a complementary organizational capability. Technology and datasets alone are purchasable; competitive value arises from the firm's ability to integrate data, ask useful questions, interpret results, and act. Analytics enhances the deployment of human capital by improving matching, development, and performance decisions. From this perspective, mediation occurs when an HR practice contributes to analytics capability and that capability improves performance.

RBV also explains why the indirect effect may differ across practices. Recruitment and training naturally create information about competencies, learning, and fit that analytics can convert into decisions. Compensation effects depend heavily on perceived fairness, reward philosophy, and employee interpretation, so an analytics pathway may be weak or negative if reward data are not integrated or if the system is not trusted. The study therefore uses RBV as its principal theoretical anchor while recognizing the behavioral role of fairness and motivation.

**Table 1 Conceptual model and expected paths**

| Predictor             |     | Mediator           | Outcome              | Expected mechanism                     |
|-----------------------|-----|--------------------|----------------------|----------------------------------------|
| Recruitment selection | and | Big data analytics | Employee performance | Better fit and evidence-based staffing |
| Compensation          |     | Big data analytics | Employee performance | Reward alignment and equity analysis   |
| Training development  | and | Big data analytics | Employee performance | Targeted learning and evaluation       |

## Methodology

### 3.1 Design, Setting and Population

A quantitative cross-sectional survey design was adopted to estimate relationships among the constructs without manipulating employee conditions. The study was conducted in Access Bank Plc branches across six Abuja area locations: AMAC, Bwari, Kuje, Gwagwalada, Kwali, and Abaji. The estimated employee population was 350, distributed as 65, 56, 42, 56, 42, and 42 respectively.

### 3.2 Sample and Sampling

A sample of 187 employees was selected. Proportionate stratified random sampling was used so that each branch location contributed respondents while preserving the population structure. Allocations were AMAC 40, Bwari 37, Kuje 27, Gwagwalada 29, Kwali 24, and Abaji 30. Of the 187 questionnaires distributed, 172 were completed and usable, yielding a response rate of 91.9%.

**Table 2: Population and sample allocation**

| Branch area | Population | Sample |
|-------------|------------|--------|
| AMAC        | 65         | 40     |
| Bwari       | 56         | 37     |
| Kuje        | 42         | 27     |
| Gwagwalada  | 56         | 29     |
| Kwali       | 42         | 24     |
| Abaji       | 42         | 30     |
| Total       | 350        | 187    |

### 3.3 Instrument and Measurement

Data were collected through a structured questionnaire using multi-item scales for recruitment and selection (RAS), compensation (COM), training and development (TAD), big data analytics (BDA), and employee performance (PEF). Each construct was represented by three retained indicators in the confirmatory factor analysis. Responses were aggregated to create construct measures for descriptive, correlational, and mediation analyses.

### 3.4 Validity and Reliability

Construct validity was assessed through confirmatory factor analysis. Standardized loadings ranged from .84 to .94. Average variance extracted exceeded .50 for every construct, composite reliability exceeded .70, and Cronbach's alpha values ranged from .862 to .903. Maximum shared variance was lower than average variance extracted, supporting discriminant validity. These results indicate that the retained indicators measured their intended constructs with satisfactory consistency.

### 3.5 Data Analysis

Pearson correlations described bivariate associations. Mediation was tested with Hayes PROCESS Model 4 using 5,000 bootstrap samples and 95% bias-corrected confidence intervals. An indirect effect was considered significant when its bootstrap interval excluded zero. Direct, indirect, and total effects were considered together to classify mediation as indirect-only, partial, or absent. The models included the other HR practices as covariates, reducing confounding among practices.

### 3.6 Ethical and Analytical Considerations

Participation was voluntary and responses were analyzed in aggregate. Because employment information can be sensitive, confidentiality and restricted access to raw data are important. The cross-sectional design supports association and statistical mediation but does not establish temporal causality. Self-report measures may introduce common-method influence, and results should be interpreted within the Abuja branch context.

## Results and Discussion

### 4.1 Measurement Results

The measurement results were strong. Recruitment and selection loadings ranged from .84 to .89; compensation from .89 to .92; training and development from .84 to .89; big data analytics from .89 to .92; and employee performance from .84 to .94. Average variance extracted ranged from .744 to .815. Composite reliability ranged from .897 to .930 and all alpha coefficients exceeded .86.

### 3. Measurement quality

| Construct                 | Loading range | AVE  | CR   | Alpha |
|---------------------------|---------------|------|------|-------|
| Recruitment and selection | .84–.89       | .749 | .900 | .866  |
| Compensation              | .89–.92       | .815 | .930 | .862  |
| Training and development  | .84–.89       | .744 | .897 | .897  |
| Big data analytics        | .89–.92       | .805 | .925 | .903  |
| Employee performance      | .84–.94       | .775 | .912 | .880  |

### 4.2 Correlation Results

Employee performance correlated positively with recruitment and selection ( $r = .284$ ,  $p < .001$ ), training and development ( $r = .321$ ,  $p < .001$ ), and big data analytics ( $r = .343$ ,  $p < .001$ ). Its correlation with compensation was negative but nonsignificant ( $r = -.090$ ,  $p = .241$ ). Recruitment and selection correlated with big data analytics ( $r = .326$ ,  $p < .001$ ), as did training and development ( $r = .293$ ,  $p < .001$ ), whereas compensation did not ( $r = -.076$ ,  $p = .322$ ). The correlations provide preliminary support for the recruitment and training mediation pathways.

**Table 4** Correlations among the study variables

| Variable | RAS    | TAD    | BDA    | COM   | PEF |
|----------|--------|--------|--------|-------|-----|
| RAS      | 1      |        |        |       |     |
| TAD      | .498** | 1      |        |       |     |
| BDA      | .326** | .293** | 1      |       |     |
| COM      | .009   | .217** | -.076  | 1     |     |
| PEF      | .284** | .321** | .343** | -.090 | 1   |

Note.  $N = 172$ . \*\*  $p < .01$  (two-tailed).

### 4.3 Mediation Results

The model predicting big data analytics was significant,  $F(3, 168) = 9.394$ ,  $p < .001$ , and explained approximately 14.7% of its variance. Recruitment and selection positively predicted analytics ( $\beta = .3380$ ,  $SE = .1254$ ,  $p < .01$ ), and training and development also had a positive effect ( $\beta = .2372$ ,  $SE = .0964$ ,  $p = .0149$ ). Compensation had a negative nonsignificant effect ( $\beta = -.1291$ ,  $SE = .0770$ ,  $p = .0957$ ). The employee-performance model was significant,  $F(4, 167) = 11.922$ ,  $p < .001$ ,  $R^2 = .193$ . Big data analytics positively predicted performance ( $\beta = .2328$ ,  $SE = .0742$ ,  $p = .0020$ ).

For recruitment and selection, the indirect effect through analytics was .0787, with a 95% bootstrap confidence interval from .0090 to .1768. Because the interval excluded zero, mediation was significant. The direct effect after including analytics was nonsignificant ( $\beta = .1385$ ,  $SE = .1232$ ,  $p = .2625$ ), so the pattern is classified as indirect-only mediation. Recruitment contributes to performance chiefly where employee and staffing data are translated into actionable insight.

For compensation, the indirect effect was  $-.0300$  ( $BootSE = .0205$ ), with a 95% confidence interval from  $-.0776$  to .0015. The interval included zero, indicating no mediation. The total effect was negative and statistically significant ( $\beta = -.1574$ ,  $p = .0400$ ), but the direct effect after analytics was nonsignificant ( $\beta = -.1273$ ,  $p = .0903$ ). The evidence does not support the proposed compensation–analytics–performance mechanism.

For training and development, the indirect effect was .0552 (BootSE = .0326), with a 95% confidence interval from .0065 to .1337. The direct effect remained significant ( $\beta = .2601$ , SE = .0944,  $p = .0065$ ), and the total effect was also significant ( $\beta = .3153$ ,  $p = .0011$ ). These results establish partial mediation: training improves performance directly and additionally through big data analytics.

**Table 5 Summary of mediation tests**

| Path            | Indirect effect | 95% bootstrap CI | Direct effect       | Conclusion        |
|-----------------|-----------------|------------------|---------------------|-------------------|
| RAS → BDA → PEF | .0787           | [.0090, .1768]   | .1385, $p = .2625$  | Indirect-only     |
| COM → BDA → PEF | −.0300          | [−.0776, .0015]  | −.1273, $p = .0903$ | No mediation      |
| TAD → BDA → PEF | .0552           | [.0065, .1337]   | .2601, $p = .0065$  | Partial mediation |

Note. Bootstrap samples = 5,000. Mediation is significant when the confidence interval excludes zero.

## Discussion

### Recruitment, analytics and performance

The indirect-only result indicates that recruitment and selection become performance-relevant through the organization's ability to use data. Merely applying recruitment procedures may not improve current employee performance unless information about applicant attributes, role requirements, placement, probation, and subsequent outcomes is integrated. Analytics creates a learning loop: the bank can identify which assessment criteria predict successful performance and refine future decisions. This supports the RBV view that complementary capabilities, rather than isolated practices, create value.

The nonsignificant direct effect does not imply that recruitment is unimportant. It indicates that, within the simultaneous model, its influence is carried through analytics. Managers should preserve structured human judgment while systematically linking recruitment evidence to later performance and retention. Such linkage can reveal effective talent sources and reduce costly mismatch.

### Compensation, analytics and performance

The absence of mediation suggests that the available compensation information was not converted into improved performance through analytics. The negative coefficients may reflect perceived inequity, weak line-of-sight between reward and contribution, or reward measures that employees cannot influence. They may also reflect contextual factors not measured in the study. Because the bivariate compensation–performance correlation was nonsignificant, conclusions about a harmful causal effect would be inappropriate.

Analytics can diagnose pay compression, market position, equity gaps, and incentive consequences, but these insights require a credible reward strategy and transparent communication. Managers should review the design and perceived fairness of compensation before increasing analytical complexity. Employee voice and qualitative evidence can explain patterns that numerical models alone cannot.

### Training, analytics and performance

Training and development showed the clearest combined pathway. The significant direct effect is consistent with human-capital logic: improved knowledge and skill support better task execution. The additional indirect effect indicates that analytics enhances this contribution by identifying needs, targeting opportunities, monitoring learning, and linking training to performance outcomes. Because the direct effect remained significant, analytics complements rather than replaces established learning processes.

The result supports an evaluation cycle that begins with competency and performance data, assigns relevant learning, monitors completion and application, and reassesses outcomes. This cycle can reduce generic training and direct limited budgets toward high-impact programmes. It should also

include managerial coaching and opportunities to apply learning, since completion data are not evidence of transfer.

### **Theoretical and Practical Implications**

The differentiated mediation results refine the resource-based explanation. Analytics is not a universal conduit through which every HR practice improves performance. Its value depends on whether a practice creates meaningful data and whether managers can act on resulting insight. Recruitment and training provide information that appears readily convertible into decisions, while compensation remains strongly dependent on fairness, design, and employee interpretation.

Practically, the bank should treat people analytics as a socio-technical capability encompassing data standards, system integration, analytical competence, governance, and managerial use. Dashboards should answer defined questions rather than display activity. Performance metrics should balance commercial, service, behavioral, and risk outcomes. Algorithms used for employment decisions should be validated and subject to human review.

### **Conclusion**

This study concludes that big data analytics selectively mediates the relationship between HRM practices and employee performance in Access Bank Plc, Abuja. Analytics fully carries the observed contribution of recruitment and selection, partially carries the contribution of training and development, and does not carry the compensation effect. Big data analytics itself is a significant positive predictor of performance, confirming its relevance as an organizational capability.

The findings reject a one-size-fits-all assumption. HR data produce value when they are connected to specific decisions and supported by credible practices. Recruitment and training benefit from feedback loops that connect inputs to later outcomes. Compensation requires attention to fairness, transparency, and motivational design before analytics can improve it. The bank should therefore integrate technology, professional judgment, governance, and employee trust.

### **Recommendations**

1. Integrate applicant, selection, placement, probation, learning, reward, and performance data in a governed HR analytics architecture with consistent definitions and access controls.
2. Track the later performance and retention of new hires to validate recruitment sources, assessments, and selection criteria, while auditing models for bias.
3. Use competency and performance evidence to identify training needs and evaluate learning at reaction, knowledge, application, and results levels.
4. Build data literacy among HR professionals and line managers so they can interpret models, question assumptions, and convert findings into responsible action.
5. Review compensation fairness, transparency, market competitiveness, and line-of-sight before using predictive tools to redesign incentives.
6. Use balanced employee-performance measures that include service quality, accuracy, collaboration, compliance, customer outcomes, and sustainable commercial results.
7. Establish privacy, security, explainability, audit, and human-review rules for analytics or AI used in consequential employment decisions.
8. Periodically evaluate analytics initiatives against documented business and employee outcomes rather than system adoption or dashboard usage alone.

### **Limitations and Future Research**

The study used cross-sectional self-report data from employees in branches of one bank within Abuja. It cannot establish temporal causality, and mediation estimates represent statistical mechanisms rather than observed change over time. Common-method bias and contextual factors may affect the estimates. The sample supports analysis of the specified model but limits subgroup comparisons.

Future studies should use longitudinal or time-lagged designs, combine employee perceptions with administrative performance records, and compare banks or regions. Researchers should examine data quality, analytical culture, trust, perceived fairness, digital readiness, and managerial capability as moderators or additional mediators. Qualitative interviews could clarify the negative compensation pattern and reveal how employees experience algorithm-supported HR decisions.

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