



## HUMAN RESOURCE ANALYTICS AND TALENT ACQUISITION PROCESS: EVIDENCE FROM NIGERIA

Tochukwu Emeka Umeh<sup>1</sup>, Hassan Yusuf (Ph.D.)<sup>2</sup>, and Oluyemi Theophilus Adeosun<sup>3</sup>.

<sup>1</sup>School of Business and Entrepreneurship, American University of Nigeria.

Email: [tochukwu.umeh@aun.edu.ng](mailto:tochukwu.umeh@aun.edu.ng)

<sup>2</sup>School of Business and Entrepreneurship, American University of Nigeria.

Email: [hassan.yusuf@aun.edu.ng](mailto:hassan.yusuf@aun.edu.ng)

<sup>3</sup>Research Fellow, Department of Economics, College of Economic and Management Sciences, University of South Africa, Unisa, South Africa.

Email: [oluyemiadeosun@gmail.com](mailto:oluyemiadeosun@gmail.com)

### Cite this article:

Tochukwu Emeka Umeh, Hassan Yusuf, Oluyemi Theophilus Adeosun (2026), Human Resource Analytics and Talent Acquisition Process: Evidence from Nigeria. International Journal of Entrepreneurship and Business Innovation 9(2), 21-40. DOI: 10.52589/IJEBI-BVWIQ7PF

### Manuscript History

Received: 17 Apr 2026

Accepted: 22 May 2026

Published: 23 Jun 2026

### Copyright © 2026 The Author(s).

This is an Open Access article distributed under the terms of Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International (CC BY-NC-ND 4.0), which permits anyone to share, use, reproduce and redistribute in any medium, provided the original author and source are credited.

**ABSTRACT:** *The integration of data analytics into human resource management, commonly referred to as human resource analytics (HRA), has emerged as a critical capability for organisations seeking to optimise their talent acquisition processes. This study examined the impact of HRA on the talent acquisition process in Nigerian organisations and investigated the challenges that moderate this relationship. A predictive survey research design was employed, with data collected from 330 HR professionals across diverse sectors of the Nigerian economy using a structured online questionnaire. Data were analysed using partial least squares structural equation modelling (PLS-SEM) 5.0. The findings revealed a positive and significant relationship between HRA and talent acquisition outcomes ( $\beta = 0.565$ ,  $p < 0.01$ ). Furthermore, challenges in adopting HRA, including a lack of top management support and data governance issues, significantly moderated the relationship between HRA and talent acquisition ( $\beta = 0.104$ ,  $p < 0.05$ ). The study concludes that while HRA significantly enhances talent acquisition in Nigeria, its effectiveness is contingent upon addressing key implementation barriers. Organisations are advised to secure leadership buy-in, comply with data privacy regulations, and invest in HRA infrastructure and capacity building, while policymakers can accelerate HRA adoption through incentives, education, and industry-wide collaboration.*

**KEYWORDS:** Data analytics, human resource analytics, people analytics, talent acquisition, talent attraction.



## INTRODUCTION

In the modern business environment, where competition is intense and technology is continually evolving, data-driven methods must replace intuition-based approaches across all areas of decision-making (Szukits & Móricz, 2023; Korherr et al., 2023), including human resources (HR) procedures. Over time, human resource functions have evolved from a lack of recognition by organisational management to a more scientifically grounded, evidence-based approach that addresses the perceived inability to quantify their contribution to business outcomes (Silva & Lima, 2018). The fusion of human resources management and data analytics, commonly referred to as human resource analytics (HRA), is a growing trend in human resources management practice (Ergle et al., 2017) and has become a transformative instrument that enables businesses to leverage data insights to optimise talent acquisition.

HRA provides a notable advantage in the global talent market due to its capacity to detect high-achieving applicants, optimise hiring procedures, forecast employee attrition, support talent acquisition, performance evaluation, career and talent management, workforce optimisation, reduce bias, and improve decision-making, among others (Quan & Raheem, 2023; Cho et al., 2023; Vadithe & Kesari, 2023). This is based on empirical data rather than mere instincts, leading to improved efficiency and effectiveness, cost minimisation, and profit maximisation (Korherr et al., 2023; Boakye & Lamptey, 2020; Ergle et al., 2017; Venkatesh, 2017). Scholars have agreed that HR analytics has enormous positive effects on business outcomes (Isson & Harriott, 2016; Boakye, 2019; Diez et al., 2020; Falletta & Combs, 2020; Zeidan & Itani, 2020; Van Vulpen, 2021); however, there is limited literature on its applicability in real-world scenarios, and in some cases, its adoption has remained remarkably slow (Ergle et al., 2017; Marler & Boudreau, 2017; Mohammed, 2019).

Some of the reasons for the slow adoption of HR analytics include the fact that most HR professionals lack the requisite abilities, knowledge, and insight to conduct successful analytics (Boakye, 2019). According to Deloitte (2015), one of the most significant capacity shortages in current HR practice is in HR analytics. Qamar and Samad (2021) also noted that most research in the HR analytics field has focused on conceptual, theoretical, and case study approaches, without addressing the challenges limiting adoption or examining the impact of HRA on specific HR practices such as talent acquisition, employee retention, and predicting employee attrition.

Despite the growing body of literature on HR analytics in developed economies, a significant research gap persists concerning its application in emerging economies, particularly Nigeria. Nigeria, with its rapidly growing youthful population and diverse workforce, presents a unique organisational environment characterised by infrastructural deficits, data governance challenges, and a transitional shift from traditional HR practices to data-driven approaches (Akinyemi & Mobolaji, 2022; Etukudo, 2019). Existing studies on HR analytics have predominantly been conducted in western contexts (Cho et al., 2023; Marler & Boudreau, 2017), leaving a critical contextual gap regarding how HRA functions, what challenges impede its adoption, and how these challenges influence its effectiveness in talent acquisition within Nigerian organisations. Furthermore, while prior research has examined HR analytics and talent acquisition separately, few studies have simultaneously investigated the moderating role of adoption challenges in the relationship between HRA and talent acquisition in an emerging-economy setting.



Guided by this gap, the study seeks to answer the following research questions:

- Rq1: to what extent does human resource analytics impact the talent acquisition process in Nigerian organisations?
- Rq2: how do the challenges of adopting HR affect the talent acquisition process in Nigeria?
- Rq3: to what extent do the challenges of adopting HRA moderate the relationship between HRA and the talent acquisition process?

This study makes three distinct contributions to literature. First, it extends the HR analytics literature by providing empirical evidence from Nigeria, an under-researched emerging economy, thereby addressing the geographical bias in existing HRA research. Second, it advances Nigerian organisational studies by examining how adoption challenges, specifically, the lack of top management support and data governance issues, moderate the effectiveness of HRA in talent acquisition. Third, it contributes to talent acquisition practice by integrating adoption challenges as a moderating construct, providing practitioners with actionable insights on barriers that must be addressed to realise the full potential of HRA in recruitment outcomes.

## LITERATURE REVIEW

### Theoretical Framework

This study is grounded in two complementary theoretical perspectives useful for understanding human resource analytics: the resource-based view (RBV) theory and contingency theory.

The resource-based view posits that organisations can achieve a long-term competitive advantage by possessing a pool of human resources that competitors cannot replicate or substitute. As a result, firms should conduct frequent employee evaluations to ensure they have the right people with the right talents in the right positions to acquire and maintain a competitive edge. According to Fossas Olalla (1999), the knowledge, competence, know-how, and skills of an organisation's personnel (i.e., human capital) may all be sources of competitive advantage. For any resource to be a source of competitive advantage for its organisation, it must be valuable, scarce, imperfectly imitable, and exploitable through the firm's organisational processes (Barney & Clark, 2007). These characteristics are commonly referred to as the VRIO framework. The authors believe that if an organisation's human resources constitute a basis for achieving and maintaining a competitive advantage, then organisations must pay special attention to how these 'useful resources' are developed (i.e., talent acquisition planning procedures) within their organisations. As a result, the C-suite should prioritise adopting technology and current tools (such as human resource analytics tools) that will enable the organisation's talent acquisition process.

Contingency theory, introduced by Fred Edward Fiedler, suggests that the most successful management approach depends on the unique situational environment. This theory is particularly relevant to HRA implementation, ensuring that analytics are purposeful and



avoid a generic, one-size-fits-all approach. In the context of talent acquisition, contingency theory underscores that effective HRA must be calibrated to the specific organisational context, including the availability of data infrastructure, leadership orientation, and the unique requirements of each role, rather than being imported wholesale from practices in other organisational or national settings.

## HR ANALYTICS AND TALENT ACQUISITION

Acikgoz (2019) defines talent acquisition as the totality of activities and efforts that influence the number and types of people who apply for a vacant, advertised job, remain in the application process until the end, and finally accept the job offered by the hiring organisation. According to Devi and Banu (2014), talent acquisition is the process of placing the appropriate person in the right job at the right time, involving the identification and encouragement of qualified applicants. Morales (2020) described it as a psychological process of attracting a sufficient number of people with appropriate credentials for a specific role. Van Niekerk (2016) further characterised it as the process by which an organisation selects and employs the best applicant while keeping time and cost in mind. Synthesising these perspectives, talent acquisition is a process that begins with the identification of recruitment requirements and ends with onboarding, encompassing all intervening actions (Devi & Banu, 2014).

Several studies have investigated the relationship between HR analytics and talent acquisition. Chiara et al. (2023) underlined the necessity of conducting talent acquisition with a focus on fairness, whereas Barathnivash (2023) emphasised that company portals are the most important medium for hiring personnel. Human resource analytics assists HR managers in formulating strategies that help the organisation outperform competitors (Pandey & Mehta, 2022). Masta (2023) underscored the need for HR professionals to adapt to rapid innovation to maintain a competitive advantage. Cho et al. (2023) provided a five-step strategy for integrating HR analytics in the public sector, emphasising data management and personnel competencies. Vadithe and Kesari (2023) focused on the efficacy of recruitment processes, with a special emphasis on the use of business portals, emphasising the value of HR analytics in talent acquisition, particularly in driving efficiency and organisational success.

According to Ejo-Orusa and Okwakpam (2018), predictive HR analytics significantly enhances HRM outcomes. Mohammed (2019) found that, although theoretical models for predicting HRA exist, their practical application in real-world settings has not been adequately investigated. Qamar and Samad (2021) identified a dearth of research on the challenges and capacities necessary for HR analytics deployment, as well as a lack of studies that employ HR analytics to explore various HR practice domains.

These studies collectively underscore the significance of fairness, data management, and technology in talent acquisition and highlight research gaps that this paper aims to address. HR analytics is increasingly used in advanced-country organisations for talent acquisition; however, implementation in Nigeria remains slow, despite its growing global popularity. Based on the empirical support from the foregoing, the following hypothesis is established:



---

**H<sub>1</sub>: Human resource analytics has a significant positive effect on the talent acquisition process.**

Despite significant academic and industry interest in HR analytics, there is still a long way to go before the benefits of data analytics are completely realised (Zeidan & Itani, 2020). HR analytics can enhance talent acquisition processes, but implementation can be challenging. HR analytics practitioners must establish networks of stakeholders throughout the organisational hierarchy to effectively deploy their tools (Bonilla-Chaves & Palos-Sánchez, 2023). According to Boakye and Lamptey (2020), specific problems inhibiting the successful application of HR analytics include a lack of HR analytics competence, a lack of top management support, and inefficient tools and data administration.

Khan et al. (2017) identified data availability, training, legacy systems, and skills shortage as important pressure points for HRA implementation. Venkatesh (2017) identified additional obstacles, including extensive data processing requirements, inadequate data quality assurance, insufficient senior management support, and analytical incompetence. Bennett (2015) identified people analytics as the second-largest capacity gap among HR practitioners. Taken together, challenges to implementing HR analytics include insufficient data, data quality concerns, lack of top management support, data governance issues, and a skill gap in analytical expertise. Based on this empirical evidence, the following hypotheses are established:

**H<sub>2</sub>: The challenges of adopting HRA have a significant negative impact on the talent acquisition process.****H<sub>3</sub>: The challenges of adopting HRA significantly moderate the relationship between HRA and the talent acquisition process.**

## METHODOLOGY

The predictive survey research design was employed in this cross-sectional study. This design was selected because it enables a systematic examination of the independent variable's influence on the dependent variable and facilitates an investigation into the benefits and challenges of using analytical tools in the talent acquisition process.

The target population comprised registered human resource professionals practising in Nigeria, with an estimated population of approximately 2,000 professionals accessible through professional HR bodies and online networks. Given the nature of the study and the practicalities of accessing a comprehensive sampling frame across Nigeria, a purposive sampling technique was employed to identify HR practitioners with direct experience in talent acquisition, supplemented by convenience sampling to reach respondents through professional networks and online platforms of HR professional community in Nigeria. This sampling approach was necessitated by the practical constraints of accessing a comprehensive population register, the high-cost implications of alternative probability sampling methods, and the timeliness of online survey administration.

The sample size was determined using the formula recommended by Krejcie and Morgan (1970) for determining sample sizes from finite populations. For a population of





approximately 2,000, the recommended sample size at a 95% confidence level is 322 respondents. To account for potential non-response and incomplete questionnaires, the target sample was increased to 395 respondents. A total of 395 standardised questionnaires were distributed, of which 330 valid responses were returned, yielding a response rate of 83.5%. This exceeds the generally accepted threshold of 60% for survey research (Baruch & Holtom, 2008), suggesting that non-response bias is unlikely to have significantly affected the findings. Nevertheless, to assess the possibility of non-response bias, early and late respondents were compared on key demographic variables, and no significant differences were found, providing additional assurance against systematic bias (Armstrong & Overton, 1977).

The study employed a structured, two-part questionnaire as the primary data collection instrument. The first section captured respondents' demographic information, including gender, age, years of HR experience, and sector of employment. The second section collected data relevant to the study's objectives, with items measuring human resource analytics, talent acquisition process outcomes, and challenges of adopting HRA. All measurement items were adapted from established and validated scales in the extant literature. The HRA construct items were adapted from Ejo-Orusa et al. (2018), the talent acquisition process items were drawn from Love (2020), and the challenges of HRA items were adapted from Tomar and Gaur (2020) and Reddy and Lakshmikeerthi (2017). All items were measured using a five-point likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

The questionnaire was pilot tested with 30 HR practitioners who were not included in the main study sample to assess its clarity, relevance, and face validity. Based on pilot feedback, minor wording adjustments were made to improve comprehension without altering the underlying constructs. The final instrument was administered online through a digital survey platform, with the link distributed via the official platform of the Nigerian HR professional community and relevant professional networks. Respondents were given a two-week window to complete the survey, with one reminder sent to non-respondents after one week.

The construct and face validity of the questionnaire were evaluated for correctness and applicability. Cronbach's alpha was used to assess internal consistency reliability. The internal consistency values for all constructs ranged from 0.702 to 0.790 (see table 3), which falls within the acceptable threshold of 0.70 (kura, 2014).

Ethical standards were rigorously observed throughout the research process. All respondents were provided with an informed consent statement at the beginning of the survey, outlining the purpose of the study, the voluntary nature of participation, and their right to withdraw at any time without penalty. Informed consent was implied through the act of proceeding to complete the survey. The anonymity and confidentiality of respondents were ensured by not collecting any personally identifiable information, and all data were stored securely on password-protected devices accessible only to the research team. Data were used exclusively for the purposes of this academic research and were handled in accordance with the Nigeria data protection regulation (NDPR, 2019) guidelines.

Data were analysed using a combination of microsoft office excel 2016 and partial least squares structural equation modelling (pls-sem) 5.0. Microsoft excel was used for data cleaning and preliminary screening, while pls-sem 5.0 was employed for both descriptive and inferential analysis. Pls-sem has become an increasingly prominent method in the social



sciences (Hair et al., 2017) owing to its flexible analysis options, limited assumptions, and user-friendliness, making it a preferred choice for advanced analysis in management research (Matthews et al., 2018; Rigdon et al., 2017). Its versatility in handling complex models and diverse constructs has been further highlighted by Akter et al. (2017). The current study examined the moderating effect of HRA adoption challenges on the relationship between HRA and the talent acquisition process. Because of its ability to handle latent variables, multiple indicators, and moderation effects, pls-sem was selected as the most appropriate analytical approach.

### Operational Definition of Key Variables

The key concepts anchoring this research are human resource analytics and the talent acquisition process.

### Human Resource Analytics (HRA)

Drawing on the literature reviewed above, HRA involves data, technology, decision-making, and people. This study defines human resource analytics as the process of acquiring and manipulating data using applicable technical tools to enable improved, evidence-based workforce management decision-making.

### Talent Acquisition Process

The talent acquisition process is the entire process of sourcing suitable candidates to join an organisation's workforce. This process encompasses identifying, attracting, screening, selecting, and interviewing credible potential employees for employment (permanent or temporary) and placing them into vacant positions within an organisation.

These operationalised variables are depicted in table 1 below:

**TABLE 1: OPERATIONALISATION OF VARIABLES**

| S/N | VARIABLE                                              | MEASUREMENT                                                                                                                                                                                                                                                                                                                                              | USED BY                 |
|-----|-------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------|
| 1   | <b>INDEPENDENT:</b><br>Human Resource Analytics (HRA) | <ul style="list-style-type: none"> <li>▪ <b>ANALYTICS INTEGRATION RATE:</b> extent of integration of HR analytics tools and methodologies within the talent acquisition process.</li> <li>▪ <b>ANALYTICS IMPACT ON HR DECISION-MAKING:</b> assessment of the influence or effectiveness of analytics in guiding talent acquisition decisions.</li> </ul> | Ejo-Orusa Et Al. (2018) |
| 2   | <b>DEPENDENT:</b><br>Talent Acquisition Process (TAP) | <ul style="list-style-type: none"> <li>▪ Quality of hire,</li> <li>▪ First-year attrition (candidate retention rate),</li> <li>▪ Cost per hire,</li> <li>▪ Offer acceptance rate,</li> <li>▪ Time to productivity,</li> <li>▪ Time to fill.</li> </ul>                                                                                                   | Love, (2020)            |
| 3   | <b>MODERATING VARIABLE:</b><br>Challenges of          | <ul style="list-style-type: none"> <li>▪ Insufficient or lack of data,</li> <li>▪ Data quality issue,</li> <li>▪ Lack of top management support,</li> </ul>                                                                                                                                                                                              | Tomar & Gaur (2020);    |



|  |     |                                                                                                                                                                  |                                      |
|--|-----|------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------|
|  | HRA | <ul style="list-style-type: none"> <li>Data governance (privacy) issues,</li> <li>HR professionals' skill gap in analytical knowledge and experience.</li> </ul> | Reddy & Lakshmik<br>eerthi<br>(2017) |
|--|-----|------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------|

*SOURCE: AUTHORS' COMPUTATION (2025)*

## RESULTS

### Demographic Characteristics of Respondents

Table 2 presents the demographic profile of the 330 respondents.

**TABLE 2: DEMOGRAPHIC CHARACTERISTICS OF THE RESPONDENTS**

| Gender                                          | Frequency  | Percent      |
|-------------------------------------------------|------------|--------------|
| Female                                          | 134        | 40.6         |
| Male                                            | 196        | 59.4         |
| <b>Age of the Respondents</b>                   |            |              |
| 18 – 24 YRS                                     | 24         | 7.3          |
| 25 – 40 YRS                                     | 286        | 86.7         |
| 41 – 60 YRS                                     | 20         | 6.0          |
| <b>Experience in HR</b>                         |            |              |
| 1 – 5YRS                                        | 238        | 72.1         |
| 6 – 10YRS                                       | 64         | 19.4         |
| 11 – 15YRS                                      | 22         | 6.7          |
| Above 15YRS                                     | 06         | 1.8          |
| <b>Sector of Respondent's Organisation</b>      |            |              |
| Professional Services                           | 96         | 29.09        |
| Not-For-Profit Organisation (CSO/NGO/INGO)      | 72         | 21.82        |
| Information And Communications Technology (Ict) | 28         | 8.48         |
| Banking And Financial Sector                    | 26         | 7.88         |
| Agriculture                                     | 22         | 6.67         |
| Healthcare                                      | 18         | 5.45         |
| Others                                          | 68         | 20.61        |
| <b>Total</b>                                    | <b>330</b> | <b>100.0</b> |

*Source: Authors' Computation (2025)*

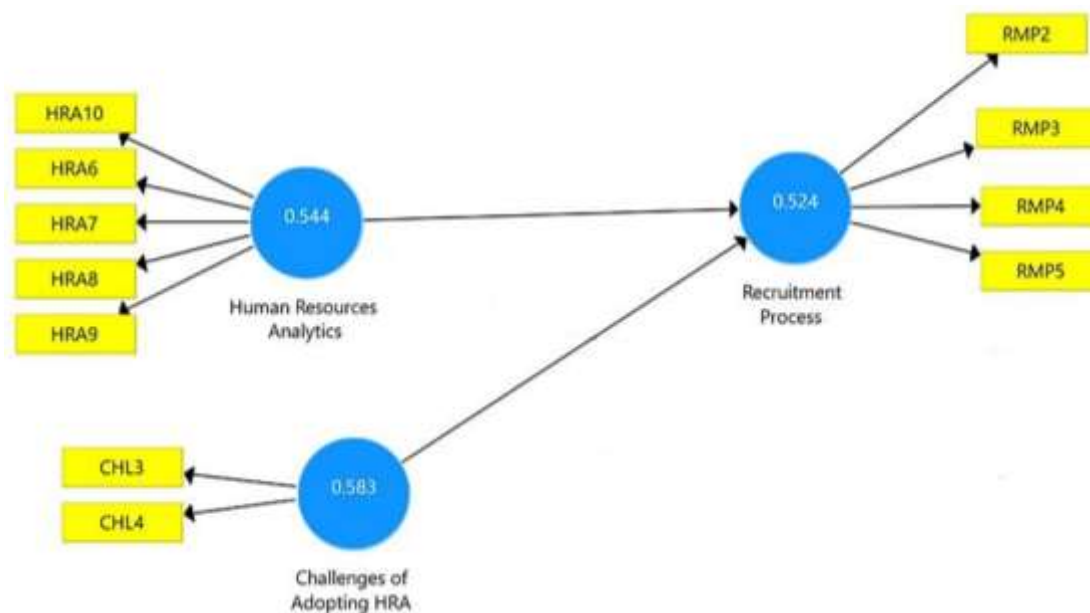
Table 2 shows that millennials and generation z constitute the majority of respondents, with 91.5% having between 1 and 10 years of HR experience. These individuals are digitally aware, open to new experiences, and adaptable to change (Kasasa, 2021; The Annie E. Casey foundation, 2021), making them suitable respondents for this research. The majority of respondents (50.9%) operate in the professional services and not-for-profit sectors, while 49.1% are well-represented across sectors such as ict, banking, agriculture, healthcare, oil and gas, tourism, and hospitality. The diversity of sectors represented supports the generalisability of the findings across Nigerian industries.



### Individual Item Reliability

Individual item reliability was assessed using the outer loadings of each construct's measures. Ten (10) of the twenty-one (21) items in the dataset were deleted because their loadings fell below 0.40, in line with the guidelines of Sarstedt et al. (2014) and Hair et al. (2017). The remaining eleven (11) items, with loadings ranging from 0.599 to 0.887, were retained for the main analysis (see figure 1: measurement model).

**Figure 1: Measurement Model**



### Internal Consistency Reliability

Table 3 presents the internal consistency reliability results.

**TABLE 3: Loadings, Composite Reliability, and Average Value Extracted Values**

| Items                             | Standardized Loadings | Cronbach's Alpha | Composite Reliability | Average Variance Extracted |
|-----------------------------------|-----------------------|------------------|-----------------------|----------------------------|
| <b>Challenges Of Adopting Hra</b> |                       | <b>0.708</b>     | <b>0.730</b>          | <b>0.583</b>               |
| CHL3                              | 0.616                 |                  |                       |                            |
| CHL4                              | 0.887                 |                  |                       |                            |
| <b>Human Resource Analytics</b>   |                       | <b>0.790</b>     | <b>0.856</b>          | <b>0.544</b>               |
| HRA10                             | 0.793                 |                  |                       |                            |
| HRA6                              | 0.704                 |                  |                       |                            |
| HRA7                              | 0.731                 |                  |                       |                            |
| HRA8                              | 0.683                 |                  |                       |                            |
| HRA9                              | 0.772                 |                  |                       |                            |



| <b>Talent Acquisition Process</b> |       | <b>0.702</b> | <b>0.815</b> | <b>0.524</b> |
|-----------------------------------|-------|--------------|--------------|--------------|
| RMP2                              | 0.755 |              |              |              |
| RMP3                              | 0.720 |              |              |              |
| RMP4                              | 0.723 |              |              |              |
| RMP5                              | 0.697 |              |              |              |

*SOURCE: AUTHORS' COMPUTATION (2025)*

Internal consistency reliability reflects the extent to which all items on a particular scale assess the same underlying construct (Sun et al., 2007). The composite reliability coefficients for each latent construct ranged from 0.730 to 0.856, exceeding the minimum acceptable threshold of 0.70, indicating strong internal consistency across all measures (Hair et al., 2011).

### **Discriminant Validity**

Table 4 presents the discriminant validity results using the htmt criterion.

**Table 4: Latent Variables Correlations and Square Roots of Average Variance Extracted**

| <b>VARIABLES</b>                 | <b>CHL</b>   | <b>HRA</b>   | <b>TAP</b>   |
|----------------------------------|--------------|--------------|--------------|
| Challenges Of Adopting HRA (CHL) | <b>0.763</b> |              |              |
| Human Resource Analytics (HRA)   | 0.015        | <b>0.738</b> |              |
| Talent Acquisition Process (TAP) | 0.177        | 0.567        | <b>0.724</b> |

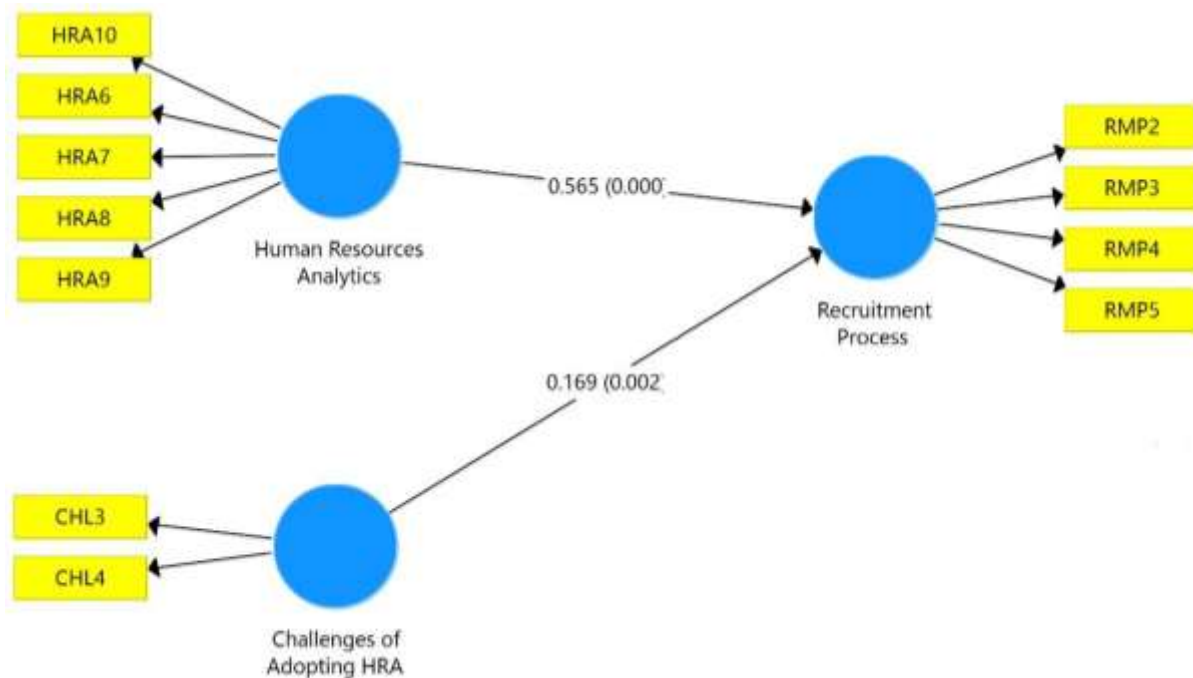
Note: Bold Diagonal Values Represent The Square Root Of Average Variance Extracted (Ave). Htmt Values Below 0.85 Confirm Discriminant Validity.

Source: Authors' Computation (2025)

Discriminant validity assesses the distinctiveness of each construct within the study's framework (Hair et al., 2019). The heterotrait-monotrait (HTMT) correlation ratio was employed, following Henseler et al. (2015), as a more robust alternative to the traditional fornell–larcker criterion. Htmt values for all construct pairs fell below the 0.85 threshold, confirming discriminant validity across all constructs in the measurement model.

### **Assessment of the Structural Model and Hypotheses Testing**

Figure 2 presents the results of the bootstrapping procedure for direct and moderating relationships.

**Figure 2: Assessment of Direct Relationships (Bootstrapping)**

**Table 5 Summarises the Hypotheses Testing Outcomes.**

**Table 5: Results of Direct and Moderating Relationships (Hypotheses Testing)**

| VARIABLES                                                                                  | BETA (B) | STD. DEV. | T STATISTIC | P VALUE | DECISION  |
|--------------------------------------------------------------------------------------------|----------|-----------|-------------|---------|-----------|
| <b>H<sub>1</sub>:</b> Human Resource Analytics => Talent Acquisition Process               | 0.565    | 0.045     | 12.687      | 0.000   | Supported |
| <b>H<sub>3</sub>:</b> Challenges Of Adopting HRA => Talent Acquisition Process             | 0.169    | 0.055     | 3.074       | 0.002   | Supported |
| <b>H<sub>5</sub>:</b> Moderating Effect Of Challenges => HRA => Talent Acquisition Process | 0.104    | 0.050     | 2.068       | 0.039   | Supported |

Note: \*\*\* P < 0.01; \*\* P < 0.05; \* P < 0.10

Source: Authors' Computation (2025)

Table 5 presents the results of hypothesis testing for both direct and moderating relationships. Direct relationships examined the impact of human resource analytics on the talent acquisition process (h<sub>1</sub>) and the effect of HRA adoption challenges on the talent acquisition process (h<sub>2</sub>). The results indicate a positive and significant relationship between HRA and the talent acquisition process ( $\beta = 0.565$ ,  $t = 12.687$ ,  $p < 0.01$ ), providing support for h<sub>1</sub>. These findings confirm that the application of HRA meaningfully enhances key talent acquisition outcomes, including quality of hire, offer acceptance rate, and time to fill.

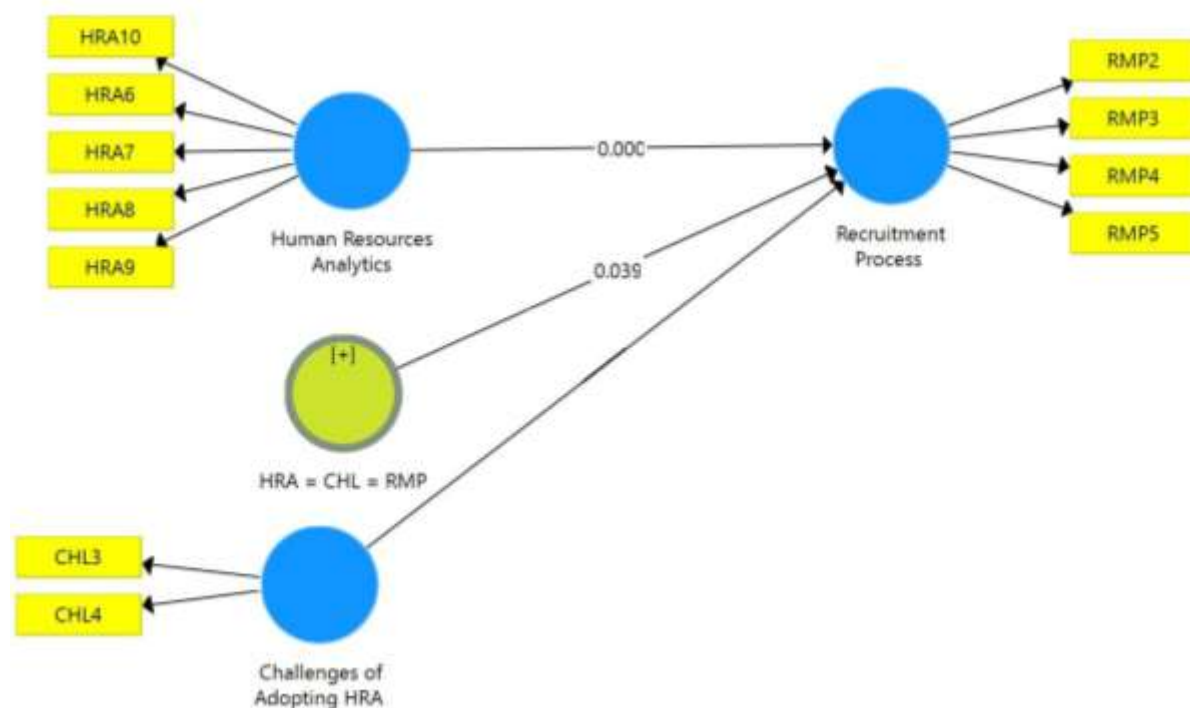
The results further show a significant relationship between the challenges of adopting HRA and the talent acquisition process ( $\beta = 0.169$ ,  $t = 3.074$ ,  $p < 0.01$ ), supporting h<sub>2</sub>. This finding indicates that barriers to HRA implementation, including lack of top management support,

data governance issues, and analytical skill gaps, exert a measurable effect on talent acquisition outcomes in Nigerian organisations.

Regarding the moderating effect ( $h_3$ ), moderation refers to situations in which the interaction between two or more variables influences the strength or direction of a relationship with a dependent variable (Hair et al., 2017). The moderating variable, i.e. the challenges of adopting HRA, may influence the intensity or direction of the relationship between HRA and the talent acquisition process. Consistent with the rule of interpretation for moderation effects, a positive path coefficient for the interaction term indicates a positive moderating effect. The results indicate a positive and significant moderating effect of challenges in HRA adoption on the relationship between HRA and the talent acquisition process ( $\beta = 0.104$ ,  $t = 2.068$ ,  $p < 0.05$ ), supporting  $h_3$ . This suggests that organisations with greater awareness of HRA challenges may be more deliberate and strategic in their implementation efforts, thereby strengthening the positive impact of HRA on talent acquisition outcomes.

In summary, all three hypotheses were supported. The findings confirm that: (a) human resource analytics has a positive and significant impact on the talent acquisition process; (b) the challenges of adopting HRA significantly affect the talent acquisition process; and (c) the challenges of adopting HRA significantly moderate the relationship between HRA and the talent acquisition process.

**Figure 3: Moderating Relationships Among the Variables (Bootstrapping Results)**





### Coefficient OF Determination ( $R^2$ )

Table 6 presents the  $R^2$  results for the endogenous construct.

**TABLE 6: Assessment of Coefficient OF Determination ( $R^2$ )**

| Endogenous VariableS       | R square | R square adjusted |
|----------------------------|----------|-------------------|
| Talent Acquisition Process | 0.350    | 0.346             |

*SOURCE: AUTHORS' COMPUTATION (2025)*

The  $R^2$  value represents the proportion of variance in the endogenous construct explained by its exogenous predictors (Henseler et al., 2016). According to Pulka et al. (2021), an  $r^2$  of 0.27 is regarded as substantial, 0.13 as moderate, and 0.02 as weak. The  $r^2$  result of 0.350 indicates that HRA and its associated adoption challenges account for 35% of the variance in the talent acquisition process, exceeding the threshold for substantial explanatory power and confirming that the model has strong predictive relevance.

## DISCUSSION

This study examined the impact of human resource analytics (HRA) on the talent acquisition process in Nigerian organisations, the effects of adoption challenges on talent acquisition, and the moderating role of these challenges in the relationship between HRA and talent acquisition. The findings carry important theoretical and practical implications that extend well beyond the statistical results presented above.

### The Impact of HRA on Talent Acquisition

The first finding, revealing a positive and significant relationship between HRA and the talent acquisition process ( $\beta = 0.565$ ,  $p < 0.01$ ), aligns with the resource-based view theory's assertion that organisations possessing valuable, rare, and inimitable resources can achieve competitive advantage (Barney & Clark, 2007). In this context, adoption of HRA in people acquisition processes is a strategic resource that, when used effectively, enhances an organisation's capacity to attract, select, and retain high-quality talent. This finding is consistent with prior research by King (2016), Ejo-Orusa and Okwakpam (2018), Boakye (2019), and Gomes (2019), who documented the positive effects of HR analytics on recruitment outcomes in various contexts.

From a theoretical standpoint, this result reinforces the rbv proposition that data-driven capabilities constitute a source of sustained competitive advantage in talent management. The substantial effect size ( $\beta = 0.565$ ) suggests that HRA is not merely a supportive tool but a core driver of talent acquisition effectiveness in Nigerian organisations. This extends the work of Marler and Boudreau (2017), whose evidence-based review of HR analytics was largely based on developed economy contexts, by demonstrating that the HRA–talent acquisition relationship holds robustly even in an emerging economy with distinct institutional and infrastructural challenges.





### **The Effect of HRA Adoption Challenges on Talent Acquisition**

The second finding revealed a significant relationship between the challenges of adopting HRA and the talent acquisition process ( $\beta = 0.169$ ,  $p < 0.01$ ). This indicates that barriers to HRA implementation, including a lack of top management support, data governance issues, and analytical skill gaps, have measurable consequences for recruitment outcomes. This finding partially corroborates Boakye's (2019) identification of competence shortages and insufficient leadership backing as key impediments, while extending the evidence to demonstrate the empirical consequence of these challenges on talent acquisition in the Nigerian setting.

Theoretically, this finding resonates with contingency theory's emphasis that the effectiveness of any management practice is contingent upon the situational context. In Nigeria, the situational context is shaped by institutional factors such as nascent data protection regulations, limited analytics infrastructure, and cultural reluctance among senior leaders to cede decision-making authority to data-driven processes. These contextual contingencies create adoption challenges that directly affect the talent acquisition process, underscoring the need for context-sensitive implementation strategies rather than the uncritical transfer of HRA practices from developed economies.

### **The Moderating Role of HRA Adoption Challenges**

The third finding concerns the moderating role of HRA adoption challenges on the relationship between HRA and talent acquisition. The positive and significant moderating effect ( $\beta = 0.104$ ,  $p < 0.05$ ) indicates that as awareness of HRA adoption challenges increases, the positive relationship between HRA and the talent acquisition process is amplified rather than diminished. While counterintuitive at first glance, this result carries meaningful theoretical implications.

From a resource-based view perspective, this positive moderation suggests that organisations that are more aware of the challenges associated with HRA adoption may be more deliberate and strategic in their implementation efforts. Rather than adopting HRA superficially or incompletely, such organisations may invest more resources in addressing barriers such as data quality issues, skills gaps, and leadership engagement, thereby creating a more robust and effective HRA capability. This interpretation is consistent with the dynamic capabilities perspective, which argues that a firm's ability to sense, seize, and reconfigure resources in response to environmental challenges is itself a source of competitive advantage (Teece, 2007). In essence, challenge awareness acts as a catalyst that prompts organisations to build stronger HRA capabilities, which in turn amplifies the positive impact of HRA on talent acquisition.

This finding also contributes to the contingency theory literature by demonstrating that the relationship between HRA and talent acquisition is not uniform across organisations but varies with the extent to which adoption challenges are recognised and proactively addressed. Organisations operating with heightened challenge awareness tend to develop more purposeful and contextually appropriate HRA practices, consistent with contingency theory's rejection of one-size-fits-all management approaches (Boakye & Lamptey, 2020; Bonilla-Chaves & Palos-Sánchez, 2023).



## CONCLUSION

This study investigated the impact of human resource analytics on the talent acquisition process in Nigerian organisations, the effect of HRA adoption challenges, and the moderating role of these challenges on the relationship between HRA and talent acquisition. The findings confirm that HRA significantly enhances talent acquisition outcomes, resulting in improved quality of hire, increased retention, reduced costs, faster time to productivity, and reduced time to fill. However, the effectiveness of HRA in Nigeria is contingent upon addressing key implementation barriers, particularly the lack of top management support and data governance issues.

## RECOMMENDATIONS

Based on the findings of this study, the following recommendations are offered for HR practitioners, organisational leaders, and policymakers:

**Secure Leadership Buy-In:** HR professionals must demonstrate the business case for HRA by linking analytics initiatives to tangible talent acquisition outcomes, including cost reductions, improved quality of hire, and revenue impact. Training senior executives on data-driven talent acquisition and aligning HRA programmes with corporate strategic goals can build the confidence and commitment necessary for sustained investment.

**Strengthen Data Governance:** transparency in data collection, usage, and storage procedures is essential for building trust with candidates and employees. Compliance with the Nigeria Data Protection Regulation (NDPR), adoption of data anonymisation techniques, and the establishment of independent data governance committees are critical to maintaining ethical standards in HRA practice.

**Invest In HRA Infrastructure And Capacity:** organisations should invest in robust analytics systems, user-friendly data tools, and the upskilling of HR personnel in data analysis, visualisation, and interpretation. Partnerships with universities and data science teams can facilitate the development of specialised curricula and advanced HRA applications.

**Policy Implications:** policymakers and regulatory agencies in Nigeria should adopt a multi-pronged strategy to accelerate HRA adoption in organisations. This includes: (a) government incentives such as tax reductions or subsidies for organisations investing in HR analytics capabilities; (b) educational initiatives that integrate HRA into university curricula for HR and business programmes; (c) strengthening the implementation of the Nigeria Data Protection Regulation (NDPR) to provide a clear regulatory framework; (d) development of industry-specific data privacy protocols for talent acquisition and HR processes; and (e) fostering public-private partnerships and industry knowledge-sharing platforms. These strategies can help Nigerian organisations harness HRA to enhance talent management, inform decision-making, and drive organisational success.



## ORIGINALITY AND VALUE

The originality of this study lies in its empirical examination of the HRA–talent acquisition relationship in the Nigerian context, an emerging economy that is substantially underrepresented in the HR analytics literature. By integrating adoption challenges as both a direct predictor and a moderator, the study addresses a specific contextual gap: the lack of empirical evidence on how barriers shape the effectiveness of HRA in talent acquisition in developing economies. The counterintuitive finding that challenge awareness positively moderates the HRA–talent acquisition relationship offers a novel theoretical contribution that extends both the resource-based view and contingency theory to the domain of HR analytics in emerging markets. This research empowers Nigerian organisations to unlock the transformative potential of HR analytics for data-driven talent acquisition success, while providing a conceptual framework applicable to other emerging economies facing similar institutional and infrastructural constraints.

## DIRECTIONS FOR FUTURE RESEARCH

Future research should explore specific strategies for overcoming data privacy concerns in the Nigerian context and examine the ethical implications of HRA in talent acquisition, particularly regarding algorithmic bias and fair hiring practices. Studies investigating the application of HRA to other HR functions beyond talent acquisition, such as employee retention, performance management, and workforce planning, would also contribute meaningfully to the literature. Longitudinal studies tracking HRA adoption over time would provide valuable insights into how organisations evolve their analytics capabilities as institutional infrastructure improves. Comparative studies across other African or emerging-market countries would further test the generalisability of the present findings.

## REFERENCES

- Acikgoz, Y. (2019). Employee Recruitment And Job Search: Towards A Multi-Level Integration. *Human Resource Management Review*, 29(1), 1–13. <https://doi.org/10.1016/j.hrmr.2018.02.009>
- Adeosun, O. T., & Adegbite, W. M. (2022). Professional Certification And Career Development: A Comparative Analysis Between Local And Foreign Certifications. *Management & Economics Research Journal*, 5(1), 1–14. <https://doi.org/10.48100/merj.2023.253>
- Akinyemi, A. I., & Mobolaji, J. W. (2022, July 18). Nigeria's Large, Youthful Population Could Be An Asset Or A Burden. *The Conversation*. <http://theconversation.com/nigerias-large-youthful-population-could-be-an-asset-or-a-burden-186574>
- Akter, S., Fosso Wamba, S., & Dewan, S. (2017). Why Is Pls-Sem Suitable For Complex Modelling? An Empirical Illustration Of Big Data Analytics Quality. *Production Planning & Control*, 28(11–12), 1011–1021. <https://doi.org/10.1080/09537287.2016.1267411>



- Aminu, I. M. (2015). Mediating Role Of Access To Finance And Moderating Role Of Business Environment On The Relationship Between Strategic Orientation Attributes And Performance Of Small And Medium Enterprises In Nigeria [Doctoral Dissertation, Universiti Utara Malaysia].
- Armstrong, J. S., & Overton, T. S. (1977). Estimating Nonresponse Bias In Mail Surveys. *Journal Of Marketing Research*, 14(3), 396–402. <https://doi.org/10.1177/002224377701400320>
- Barathnivash, V. (2023). A Study On The Effectiveness Of The Recruitment Process. *Met Management Review*, 10(2), 13–18. <https://doi.org/10.34047/Mmr.2020.10202>
- Barney, J. B., & Clark, D. N. (2007). *Resource-Based Theory: Creating And Sustaining Competitive Advantage*. Oxford University Press.
- Baruch, Y., & Holtom, B. C. (2008). Survey Response Rate Levels And Factors In Organizational Research. *Human Relations*, 61(8), 1139–1160. <https://doi.org/10.1177/0018726708094863>
- Bennett, C. (2015). HR And People Analytics: Stuck In Neutral. In *Deloitte's Global Human Capital Trends 2015: Leading In The New World Of Work*. Deloitte University Press. <https://www2.deloitte.com/content/www/us/en/insights/focus/human-capital-trends/2015/people-and-hr-analytics-human-capital-trends-2015.html>
- Boakye, A. (2019). An Exploratory Study Of Human Resources (HR) Analytics: Implications For Human Resource Management Practice [Master's Thesis, University Of Ghana]. <http://ugspace.ug.edu.gh>
- Boakye, A., & Lamprey, 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>
- Bonilla-Chaves, E. F., & Palos-Sánchez, P. R. (2023). Exploring The Evolution Of Human Resource Analytics: A Bibliometric Study. *Behavioral Sciences*, 13(3), 244. <https://doi.org/10.3390/Bs13030244>
- Chiara, A., Marina, F., & Gioia, V. (2023). Analysis Of Human Resource Recruitment From An Islamic Perspective. *Journal Islamic Economic Minangkabau*, 1(1), 61–69. <https://doi.org/10.55849/Jiem.V1i1.78>
- Cho, W., Choi, S., & Choi, H. (2023). Human Resources Analytics For Public Personnel Management: Concepts, Cases, And Caveats. *Administrative Sciences*, 13(2), 41. <https://doi.org/10.3390/Admsci13020041>
- Deloitte. (2015). *Global Human Capital Trends 2015: Leading In The New World Of Work*. <https://www2.deloitte.com/AU/en/Pages/Human-Capital/Articles/Global-Human-Capital-Trends-2015-Leading-New-World-Work.html>
- Devi, M. B. R., & Banu, P. V. (2014). Introduction To Recruitment. *Ssrg International Journal Of Economics And Management Studies*, 1(2), 1–4.
- Diez, F., Bussin, M., & Lee, V. (2020). *Fundamentals Of HR Analytics: A Manual On Becoming HR Analytical* (1st Ed.). Emerald Publishing.
- Ejo-Orusa, H., & Okwakpam, J. A. (2018). Predictive HR Analytics And Human Resource Management Amongst Human Resource Management Practitioners In Port Harcourt, Nigeria. *Global Scientific Journal*, 6(7), 23.
- Ergle, D., Ludviga, I., & Kalviņa, A. (2017). Turning Data Into Valuable Insights: The Case Study In An Aviation Sector Company. *Cbu International Conference Proceedings*, 5, 294–299. <https://doi.org/10.12955/Cbup.V5.941>



- Etukudo, R. (2019). Strategies For Using Analytics To Improve Human Resource Management [Doctoral Dissertation, Walden University]. <https://Scholarworks.Waldenu.Edu/Dissertations/6557>
- Falletta, S. V., & Combs, W. L. (2020). The HR Analytics Cycle: A Seven-Step Process For Building Evidence-Based And Ethical HR Analytics Capabilities. *Journal Of Work-Applied Management*, 13(1), 51–68. <https://doi.org/10.1108/Jwam-03-2020-0020>
- Fiedler, F. E. (1967). *A Theory Of Leadership Effectiveness*. McGraw-Hill.
- Fossas Olalla, M. (1999). The Resource-Based Theory And Human Resources. *International Advances In Economic Research*, 5(1), 84–92. <https://doi.org/10.1007/Bf02295034>
- Gomes, O. (2019, August 12). 8 Key Benefits Of HR Analytics. Talview. <https://Blog.Talview.Com/8-Key-Benefits-Of-HR-Analytics>
- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A Primer On Partial Least Squares Structural Equation Modeling (Pls-Sem)* (2nd Ed.). Sage Publications.
- Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). Pls-Sem: Indeed, A Silver Bullet. *Journal Of Marketing Theory And Practice*, 19(2), 139–152. <https://doi.org/10.2753/Mtp1069-6679190202>
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. R. (2019). When To Use And How To Report The Results Of Pls-Sem. *European Business Review*, 31(1), 2–24. <https://doi.org/10.1108/Ebr-11-2018-0203>
- Henseler, J., Hubona, G., & Ray, P. (2016). Using Pls Path Modeling In New Technology Research: Updated Guidelines. *Industrial Management & Data Systems*, 116(1), 2–20. <https://doi.org/10.1108/Imds-09-2015-0382>
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A New Criterion For Assessing Discriminant Validity In Variance-Based Structural Equation Modeling. *Journal Of The Academy Of Marketing Science*, 43(1), 115–135. <https://doi.org/10.1007/S11747-014-0403-8>
- Isson, J. P., & Harriott, J. (2016). *People Analytics In The Era Of Big Data: Changing The Way You Attract, Acquire, Develop, And Retain Talent*. Wiley.
- Kasasa. (2021, July 6). Boomers, Gen X, Gen Y, Gen Z, And Gen A Explained. The Kasasa Exchange. <https://www.kasasa.com/exchange/articles/generations/gen-x-gen-y-gen-z>
- Khan, P. H., Sultana, A., & Reddy, T. N. (2017). Review On HR Analytics: An Emerging Scale For Evaluation Of Human Assets. *International Journal Of Management And Social Science*, 5(8), 140–145.
- King, K. G. (2016). Data Analytics In Human Resources: A Case Study And Critical Review. *Human Resource Development Review*, 15(4), 487–495. <https://doi.org/10.1177/1534484316675818>
- Korherr, P., Kanbach, D. K., Kraus, S., & Jones, P. (2023). The Role Of Management In Fostering Analytics: The Shift From Intuition To Analytics-Based Decision-Making. *Journal Of Decision Systems*, 32(3), 600–616. <https://doi.org/10.1080/12460125.2022.2062848>
- 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>
- Kura, K. M. (2014). *Organisational Formal Controls, Group Norms And Workplace Deviance: The Moderating Role Of Self-Regulatory Efficacy* [Doctoral Dissertation, Universiti Utara Malaysia].





- Love, A. (2020, August 19). 8 Crucial Recruitment Metrics For 2020. Hirevue. <https://www.hirevue.com/blog/hiring/eight-recruitment-metrics-that-matter>
- Marler, J. H., & Boudreau, J. W. (2017). An Evidence-Based Review Of HR Analytics. *The International Journal Of Human Resource Management*, 28(1), 3–26. <https://doi.org/10.1080/09585192.2016.1244699>
- Masta, K. (2023). Human Resource Analytics. *International Journal For Multidisciplinary Research*, 5(3). <https://doi.org/10.36948/ijfmr.2023.V05i03.3638>
- Matthews, L., Hair, J., & Matthews, R. (2018). Pls-Sem: The Holy Grail For Advanced Analysis. *Marketing Management Journal*, 28(1), 1–13.
- Mohammed, A. Q. (2019). HR Analytics: A Modern Tool In HR For Predictive Decision Making. *Journal Of Management*, 6(3). <https://doi.org/10.34218/Jom.6.3.2019.007>
- Morales, S. D. S. (2020). The Application Of Artificial Intelligence (Ai) In The Recruitment Process: An Approach To The Application Guideline And Future Implications.
- Pandey, S., & Mehta, J. (2022). HRpa: Human Resource Prediction Analytics. In 2022 Third International Conference On Intelligent Computing Instrumentation And Control Technologies (Icici) (Pp. 721–726). Ieee. <https://doi.org/10.1109/Icici254557.2022.9917576>
- Pulka, B. M., Ramli, A., & Mohamad, A. (2021). Entrepreneurial Competencies, Entrepreneurial Orientation, Entrepreneurial Network, Government Business Support, And Smes Performance: The Moderating Role Of The External Environment. *Journal Of Small Business And Enterprise Development*, 28(4), 586–618. <https://doi.org/10.1108/Jsbed-12-2018-0390>
- Qamar, Y., & Samad, T. A. (2021). Human Resource Analytics: A Review And Bibliometric Analysis. *Personnel Review*, 50(5), 1085–1112. <https://doi.org/10.1108/Pr-04-2020-0247>
- Quan, T. Z., & Raheem, M. (2023). Human Resource Analytics On Data Science Employment Based On Specialized Skill Sets With Salary Prediction. *International Journal Of Data Science*, 4(1), 40–59. <https://doi.org/10.18517/ijods.4.1.40-59.2023>
- Reddy, D. P. R., & Lakshmikeerthi, P. (2017). HR Analytics: An Effective Evidence-Based HRm Tool. *International Journal Of Business And Management Invention*, 6(7), 23–34.
- Rigdon, E. E., Sarstedt, M., & Ringle, C. M. (2017). On Comparing Results From Cb-Sem And Pls-Sem: Five Perspectives And Five Recommendations. *Marketing Zfp – Journal Of Research And Management*, 39(3), 4–16. <https://www.jstor.org/stable/26426850>
- Sarstedt, M., Ringle, C. M., Smith, D., Reams, R., & Hair, J. F. (2014). Partial Least Squares Structural Equation Modeling (Pls-Sem): A Useful Tool For Family Business Researchers. *Journal Of Family Business Strategy*, 5(1), 105–115. <https://doi.org/10.1016/J.jfbs.2014.01.002>
- Silva, M. S. A. E., & Lima, C. G. D. S. (2018). The Role Of Information Systems In Human Resource Management. In M. Pomffyova (Ed.), *Management Of Information Systems*. Intechopen. <https://doi.org/10.5772/Intechopen.79294>
- Sun, W., Chou, C. P., Stacy, A. W., Ma, H., Unger, J., & Gallaher, P. (2007). Sas And Spss Macros To Calculate Standardised Cronbach's Alpha Using The Upper Bound Of The Phi Coefficient For Dichotomous Items. *Behavior Research Methods*, 39(1), 71–81. <https://doi.org/10.3758/Bf03192845>
- Szukits, Á., & Móricz, P. (2023). Towards Data-Driven Decision Making: The Role Of Analytical Culture And Centralisation Efforts. *Review Of Managerial Science*. <https://doi.org/10.1007/S11846-023-00694-1>





- Teece, D. J. (2007). Explicating Dynamic Capabilities: The Nature And Microfoundations Of (Sustainable) Enterprise Performance. *Strategic Management Journal*, 28(13), 1319–1350. <https://doi.org/10.1002/Smj.640>
- The Annie E. Casey Foundation. (2021, January 13). What Are The Core Characteristics Of Generation Z? The Annie E. Casey Foundation. <https://www.aecf.org/blog/what-are-the-core-characteristics-of-generation-z>
- Tomar, S., & Gaur, M. (2020). HR Analytics In Business: Role, Opportunities, And Challenges Of Using It. *Journal Of Xi'an University Of Architecture & Technology*, 12(7), 1299–1306.
- Vadithe, R. N., & Kesari, B. (2023). Human Resource Analytics On Recruitment: A Systematic Review. *Journal Of Development Economics And Management Research Studies*. <https://doi.org/10.53422/Jdms.2023.101803>
- Van Niekerk, R. (2016). The Nature And Value Of Recruitment And Talent Management Analytics: A Systematic Literature Review [Unpublished Master's Thesis]. University Of Pretoria. <https://repository.up.ac.za/handle/2263/60526>
- Van Vulpen, E. (2021, June 18). What Is HR Analytics? AiHR. <https://www.aihr.com/blog/what-is-hr-analytics/>
- Venkatesh, A. N. (2017). Conceptualising HR Analytics Practices For Healthier Organisational Performance: A Framework-Based Analysis. *International Journal Of Engineering, Business And Enterprise Applications*, 22(1), 6–10.
- Zeidan, S., & Itani, N. (2020). HR Analytics And Organisational Effectiveness. *International Journal On Emerging Technologies*, 11(2), 683–688.