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Human resource analytics and organizational performance: an empirical study

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Abstract

This study investigates the connection between human resource analytics (HRA) and organizational performance in Saudi Arabian companies, focusing on three areas: employee engagement analytics, talent acquisition analytics, and manpower planning analytics. A quantitative descriptive research approach was employed, and 281 employee responses were obtained through a web-based survey using simple random sampling. Data were analyzed using SPSS. The results of the multiple regression analysis indicated a statistically significant model, $F(3, 277) = 56.55$, $p < .001$, accounting for 38.0% of the variance in organizational performance ($R^2 = 0.380$; adjusted $R^2 = 0.373$). Among the three dimensions, manpower planning analytics exhibited the strongest positive relationship with organizational performance ($\beta = 0.280$, $p < .001$), followed by employee engagement analytics ($\beta = 0.222$, $p = .001$) and talent acquisition analytics ($\beta = 0.211$, $p = .002$). These findings demonstrate the strategic relevance of HRA to organizational performance in Saudi Arabia while enriching the empirical literature through evidence from a context that remains insufficiently examined. The study also provides practical insights for Saudi organizations seeking to strengthen data-driven HR decision-making that supports the strategic priorities of Saudi Arabia's Vision 2030.

Keywords: Human resource analytics, Organizational performance, Employee engagement analytics, Talent acquisition analytics, Manpower planning analytics

1. Introduction

Rapid technological developments have strengthened competition in global markets, compelling businesses to modify constantly to changing market conditions. As a result, it has also created awareness of the value of human capital as one of the most critical components of an organization's competitive advantage. Due to this paradigm shift, the modern corporate landscape is being redefined [1]. As a result of the increasing emphasis placed on competitive advantages by organizations, human resource analytics (HRA) have emerged as tools to assist organizations in utilizing data-driven insights to provide direction for strategic human resource decisions [2]. As explained by [3], Human resource (HR) analytics utilizes statistical and analytical methods applied to employee data to assist organizations in improving human capital outcomes. The movement from intuition-based practices to evidence-based practices within human resources is especially vital in developing markets like Saudi Arabia, where there will be considerable impact on organizational performance. Therefore, this context presents an opportunity to examine the association between HRA and organizational performance. Saudi Arabia's Vision 2030 serves as a strategic economic plan directed to varying the national economy, decreasing reliance on oil, and fostering a knowledge-based society. Vision 2030 signifies a significant economic change in the Kingdom of Saudi Arabia [4]. An important component of this transformation is understanding that sustainable growth relies on good workforce management and human capital development.

Saudi companies face unique challenges. Improving productivity, closing skills gaps, competing globally, and creating jobs are some of those challenges [5]. Overcoming those challenges will require new approaches to human resource management (HRM); therefore, Saudi firms will need to adopt HR analytics. Utilizing data, they can make better decisions regarding employee training, recruitment, engagement, and performance management [6].

1.1. Literature review

1.1.1. Human resource analytics

Human Resource Analytics is referred to by many names including people, workforce or talent Analytics. The use of analytical techniques applied to a variety of workforce metrics and data enables organizations to optimize their performance and inform better decision-making [7]. HR analytics has evolved from being simply descriptive reports about an organization's history to predictive and prescriptive analytics [8]. First, human resource information systems (HRIS) provided basic administrative functions and reporting related to compliance matters and provided the basic historical workforce data on how much staff was hired and retained, along with payroll. As Business Intelligence tools developed, organizations began to recognize patterns in their workforce data, which allowed them to conduct more detailed descriptive analytics [3].

Modern HR analytics now encompasses additional areas of focus, namely predictive and prescriptive capabilities to assist organizations in optimizing their HR strategies and forecasting future changes within their workforces [9]. Predictive HR analytics is the use of statistical modelling and machine learning techniques to estimate outcomes such as turnover and performance. Prescriptive HR analytics recommends specific actions that will achieve desired outcomes. The shifting focus of HR analytics follows broader trends in business analytics and the increasing availability of workforce data from multiple sources, including HRIS, employee surveys, and digital workplace tools [10].

Recent studies are increasingly framing HR analytics as a strategic organizational strength rather than just an administrative reporting task. Higher levels of people analytics maturity have been associated with stronger organizational performance and more systematic data-driven workforce decision-making [7]. Recent literature has likewise emphasized the contribution of HR analytics to organizational performance through improved use of workforce data and analytical capabilities [11]. Predictive analytics and workforce-planning applications have become particularly prominent, reflecting the movement of HR analytics toward more strategic and forward-looking applications [9], [12]. Organizational support and analytical capability remain important conditions for realizing these benefits [13]. The integration of human resource management, organizational behavior, statistics, and information systems is conceptualized as of human resource analytics [14], it represents the growing shift toward data-driven decision- making in HRM versus reliance on subjectivity and public opinion. Data from organizational behavior provides insight into the psychological and social factors that affect the attitudes and behaviors of employees. Quantitative analyses (statistical methods) are used to test hypotheses and examine relationships among variables in HR analytics. Additionally, HR analytics uses technology to collect, manage, analyze, and present workforce data.

HR analytics is becoming a strategic tool for HR managers by providing evidence to support managerial decision-making via projection modeling techniques, analytical software, and employee-related data. Research has demonstrated the utilization of HR analytics in areas such as staffing, employee engagement, and talent acquisition [15]. Research has also identified several different classifications of HR analytics (operational, tactical, and strategic), with strategic examples of HR analytics including workforce planning, staffing, and employee engagement [16].

A fundamental philosophical basis for HR analytics is that all organizational workforce information can be used as a source of knowledge about the business and its elements that are involved with the ability to produce results. As such, this information can be used by management to strategically develop and implement plans [17]. Many analytical tools identify trends and connections within an organization that may not be recognized through day-to-day operations or the review of routine reports. Most predictive tools allow organizations to foresee events that will occur in the future based on historical data and allow them to proactively address issues that could negatively impact organizational performance. Overall, HR analytics has many benefits, including better recruitment processes, higher employee retention, increased talent development, and, ultimately, improved organizational success [11].

However, there are many challenges associated with utilizing HR analytics. Organizations need to address issues related to governance, ethics, privacy, and data quality [18]. To effectively utilize HR analytics, organizations must invest in training or hire analytic experts, since the effective use of analytics requires specialized skills that conventional HR teams often lack [12]. Further, incorporating analytics into decision-making also requires a cultural shift for managers to trust and act upon analytics-based insights [19]. These issues may be especially challenging for emerging markets such as Saudi Arabia, where HR analytics continues to evolve.

1.1.2. Organizational performance in the Saudi Arabian context

Organizational performance is a critical component for all Saudi-based organizations as they are undergoing broad-reaching changes through their implementation of Vision 2030. Performance encompasses both non-financial and financial aspects. Examples of the non-financial aspects of performance are process efficiency, employee productivity and morale, and service quality and sustainability. Financial performance includes financial output (such as profitability, revenue growth), operational performance (such as product quality, efficiency), and market performance (such as market share, customer satisfaction, and competitor analysis). Human capital performance is defined as employees' contribution to productivity, job retention, and overall morale [1]. The relative importance of these different aspects will vary depending upon the specific industry, strategy, and stakeholders. However, there are several contextual issues that have been identified within Saudi Arabian research studies as being influential in performance outcomes. These include digital transformation. A recent Saudi Arabian-based study found that most firms believed that implementing digital transformation strategies would lead to enhanced organizational performance. It achieved such performance improvements by improving the efficiency of Saudi-based firms, creating higher levels of customer service quality, and providing greater support for innovation [20].

There are many factors limiting or reducing organizational performance within the labor market in Saudi Arabia. One factor is that the Saudization policy has made it difficult for international firms (multinational corporations [MNCs]) and domestic firms to use foreign workers. MNCs and local firms that have implemented strategic human resource management (SHRM), through tools such as HR analytics, seem to be outperforming their competitors [21]. In fact, research by [5] showed that if an organization can manage its workforce effectively, then its employees will be more satisfied and committed, leading to lower employee turnover and higher productivity, which lead to better overall organizational performance.

Research regarding small and medium-sized enterprises (SMEs) within Saudi Arabia also indicates that smart technologies enhance digital transformation and business success. Therefore, it is imperative that organizations create ready and supportive environments to enable successful technology integration [22].

The digital revolution is another major obstacle to organizational performance in Saudi Arabia. For example, [23] examined the influence of digital transformation on employee satisfaction in the private sector in Saudi Arabia, and they discovered strong positive impacts. They found that organizations utilizing digital HR tools (i.e., analytics platforms) reported high levels of employee satisfaction. In turn, employee with higher satisfaction is positively associated with organizational performance and employee retention. Additionally, [24] studied how technological development influences HR practices in Saudi companies. He determined that their utilization resulted in greater HR efficiency and, ultimately, better organizational outcomes.

1.2. Theoretical framework

1.2.1. Resource-based view (RBV)

One of the theory-based approaches to understanding the linkages between HR analytics and organizational performance is the resource-based view (RBV). The RBV is a theory that describes how companies obtain long-term competitive advantages as a result of their possession of resources and capabilities that have the characteristics of being valuable, rare, hard to duplicate, and non-substitutable [1]. Based on this concept, HR analytics is viewed by some as an example of a company's capability to take workforce data and turn it into strategic business intelligence. Therefore, the value derived from an organization's employee data is not just derived from having the data itself, but from its ability to take the workforce data and apply the knowledge derived from it to make informed decisions regarding the workforce.

These three capabilities are examples of ways in which an organization can utilize the above-described capability. The first capability referred to here is employee engagement analytics. This type of capability allows organizations to take systematic and organized views about how employees feel about their work environment. Talent acquisition analytics is another example of a capability that enables organizations to apply data-driven decision-making techniques when selecting potential candidates for employment. Manpower planning analytics enables organizations to forecast future staffing needs and allocate human capital accordingly. Each of these types of capabilities will enhance or improve existing human resource functions within an organization and thus contribute positively to overall organizational performance. Therefore, the RBV is applicable to this research due to the fact that it provides the rationale for why differences in organizations' abilities to use HR analytics capabilities may correspond with differences in organizational performance.

1.2.2. Human capital theory

Human capital theory offers an alternative viewpoint by focusing on the value of employee knowledge, skills, capabilities, and development to the organization [1]. Through this viewpoint, HR analytics can provide organizations with data to enable them to make more informed decisions about acquiring, developing, engaging, and utilizing their human capital. Rather than viewing all employee investment as equal, HR analytics will allow organizations to determine where human capital resources are needed and how current capabilities can best align with organizational needs. This theory is most directly applicable to each of the three HR analytics dimensions assessed within this research. Employee engagement analytics refers to the successful use and retention of human capital currently available to the organization; talent acquisition analytics refers to finding and acquiring appropriate human capital; manpower planning analytics refers to the deployment and future availability of human capital. Consequently, the RBV and human capital theory provide complementary insights into the expected positive link between these HR analytics dimensions and organizational performance. The theoretical foundation outlined here is likewise pertinent to Saudi Arabia. In Saudi Arabia, the development of human capital is a vital component of Vision 2030 [24].

1.3. Hypotheses development

1.3.1. Employee engagement analytics

Employee engagement refers to a workplace psychological state, which includes energy, dedication, and immersion in an employee's work. It also leads to positive outcomes for individuals and employers [1]. Analytics related to employee engagement include systematic measurement, analysis, and prediction regarding an organization's or department's employee engagement levels, including their underlying causes. To assess employee engagement, organizations use a variety of methods, including data collected during employee surveys and employee attitudinal assessments, as well as behavior-based metrics such as, but not limited to, attendance, participation, and productivity [25]. These analytics allow organizations to build work environments that support discretionary effort and motivation toward the organization through providing actionable insights into the level of engagement among their workforce.

Research indicates that the impact of employee engagement analytics has a direct relationship with a corporation's success because employees who are engaged produce more output at a higher quality than those who are disengaged. Furthermore, research suggests that employees who are engaged exhibit less absenteeism and demonstrate greater loyalty to the mission of the organization [1]. Chatbots and other artificial intelligence (AI)-powered tools are being used to provide continuous interaction between HR departments and employees. The purpose of this type of tool is to offer quick responses to employee questions and concerns, improve communication, and enhance the new hire process [26]. There is evidence to suggest that companies that utilize AI-based HR practices will see improvements in employee satisfaction, engagement, and retention as a result of better interactions and more adaptable HR processes [26], [27]. Companies in Saudi Arabia, especially in the private sector and among younger employees, continue to struggle with motivating employees and creating employee engagement. However, there may be a solution through the use of data-driven engagement analytics. [1] Demonstrated that HR analytics increases employee engagement, thereby improving organizational performance. Additionally, [25] found that sophisticated analytics can result in higher employee retention and engagement, ultimately enhancing organizational performance. By recognizing and tackling factors that influence employee engagement, organizations can foster an atmosphere that encourages discretionary effort. As such, it is vital for organizations operating in Saudi Arabia to consider utilizing engagement analytics given the country's desire to enhance productivity and employment levels under Vision 2030 [24]. The study, therefore, suggests that.

H1: Employee engagement analytics is positively associated with organizational performance from the perspective of employees.

1.3.2. Talent acquisition analytics

The use of data-driven approaches in talent acquisition helps enhance both the procedure drawing in and keeping the top candidates for an organization [28]. The techniques used include identifying which recruitment channel is the most successful at attracting high-quality applicants, using forecasting methods to estimate the quality of each applicant pool, reducing the time it takes to hire a new employee, and evaluating the success of the hiring process. Organizations collect data from many different types of data sources, including applicant tracking systems (ATS), assessment results, formal interview processes, and historical performance records after the individual has been hired. Organizations can then leverage this collected data to improve current talent acquisition strategies and build predictive models for future hires [29]. Analytics related to talent acquisition are primarily beneficial for identifying the most productive recruiting channels to attract top performers. For example, HR professionals compare how employees who were attracted via different channels (e.g., job boards, employee referrals, and campus recruiting, social media) perform on the job and remain employed by the organization. Based on this information, companies are able to make better investments. In addition, predictive tools that measure a candidate's fit for the position provide confidence in making informed business decisions [28].

In Saudi Arabia, the significance of talent acquisition analytics cannot be emphasized enough due to the significant barriers that exist within the country regarding obtaining skilled laborers. Due to the lack of available qualified individuals, the competition for skilled workers creates a competitive environment. According to [6], the strategies of recruitment and selection significantly impact organizational performance in Saudi telecommunications companies. Moreover, based on their findings, a one percent improvement in these two areas leads to a 1.637 percent gain in organizational performance. Similarly, [30] showed that e-recruitment can contribute to the success of the company through its ability to find employees who match the organization's strategic goals and culture using data-driven methods. Also, [31] found that, in the case of Saudi telecommunications, the impact of best practices for talent management, including talent acquisition, effective onboarding, employee development, and organizational support, was positive toward both employee performance and overall company success.

HR analytics is now an important tool for teams to make knowledgeable choices about staffing strategy. According to recent studies, it appears that more and more Saudi organizations are beginning to implement HR analytics to help manage their talent, aid in decision-making, and support Saudi Arabia's economic diversification activities [32], [33]. Thus, the study suggests the following hypothesis:

H2: Talent acquisition analytics is positively associated with organizational performance from the perspective of employees.

1.3.3. Manpower planning analytics

Manpower planning, or strategic manpower planning [34], is a process of making informed decisions regarding the correct number of staff, with appropriate levels of skill, in the correct job roles, at the correct time. Strategic manpower planning provides an overview of both immediate operational requirements and long-term strategic workforce objectives. Examples of strategic uses of manpower planning include maintaining employee skill inventories, developing succession planning strategies, analyzing potential gaps or surpluses of supply and demand for specific skills and/or positions, and forecasting demand [12]. Demand forecasting is a technique used to project an organization's future workforce demands through various methods, including projective modeling, historical data, and an examination of organizational business plans. The use of forecasting tools examines the impact of corporate initiatives such as restructuring, attrition, retirement, and new hiring or growth on the future workforce [34].

Supply analysis examines an organization's current workforce as well as its existing talent pool to determine possible candidates to fill critical or essential roles, which are anticipated to be vacant due to turnover and/or other reasons. Additionally, supply analysis identifies areas where recruiting externally will be necessary. A gap analysis compares an organization's projected demand for employees with the available workforce supply. Through this comparison, it can be determined whether there will be a surplus or shortage of qualified employees in certain departments or functions [34].

Finally, situation planning allows an organization to analyze the potential outcomes of differing business situations and assess how these will affect the future workforce. This is useful for strategic decision-making when uncertainty exists within an organization [9]. Machine learning methods have been incorporated into manpower planning analytics to improve the predictive power of forecasts and to identify latent patterns of employment. Survival analysis has also been used to assess the probability of turnover (attrition) for an individual as well as from a team standpoint by analyzing employee tenure.

Network analysis is used to determine who possesses critical knowledge or may be a candidate for succession. Skills analysis provides the link between the organization's skills profile and future expected skill shortages. All these analytic tools provide organizations with an opportunity to proactively manage their workforces and move away from simply being reactive when it comes to managing their workforces [18]. There is research showing that more advanced manpower planning analytics results in enhanced organizational performance. For example, [34] found that AI-based recruitment strategies and forecasting algorithms assist organizations in anticipating their upcoming staffing needs and creating proactive plans to meet those future talent demands.

Manpower planning analytics is designed to assist organizations in addressing challenges associated with nationalizing the workforce as a result of economic growth in Saudi Arabia [35]. Organizations must strike a balance between maintaining operational capabilities and competitiveness and achieving Saudization objectives. In ref. [36] the need for strategic manpower planning to create a continuous employee flow for small- to large-sized businesses was identified; specifically, the study focused on analytical techniques used by organizations to project skill demand and build internal talent pools, which would reduce dependency on external labor markets. Therefore, this study presents the following hypothesis.

H3: Manpower planning analytics is positively associated with organizational performance from the perspective of employees.

2. Research method

2.1. Sampling and sample selection

A probability-based simple random sampling design was utilized to draw participants from a target population of employees (N = 430). Simple random sampling was chosen to ensure that all members of the defined target population had an equal chance of being selected and thus minimize the potential for systematic bias in participant selection. Electronic data collection was conducted from December 2025 through April 2026. A total of 281 usable responses were collected during this time frame. These responses represent roughly 65% of the total target population. The sample size exceeded commonly cited minimum sample sizes for multiple regression studies [37]. Tabachnick and Fidell [38] provide guidelines regarding the appropriate number of cases for conducting multiple regression studies. They indicate that $N \geq 50 + 8m$, where m refers to the number of predictor variables. When m = 3, they suggest that there be at least 74 cases. Conversely, Green [39] suggests that $n \geq 104 + m$. In accordance with Green's suggestion, 107 cases would be required. Probability-based sampling is also consistent with standard sampling principles [40]. Krejcie and Morgan [41] indicate that for a population of 430 at a 95% confidence level, a sample of approximately 201 individuals is sufficient. As the study had 281 participants, the sample was deemed large enough for the planned analyses.

2.2. Pilot study

A pilot study with 30 participants was carried prior to the main data collection to evaluate the clarity, understanding, relevance, and initial reliability of the questionnaire. The pilot study allowed for an assessment of whether or not survey participants could easily understand and/or provide accurate answers regarding all of the questions. According to the literature on survey methodology [42], [43], this number is large enough to be useful as a preliminary test.

2.3. Measurement

The current study utilized a multi-item scale that was derived from existing measures of HRM, as well as analytics. The items were adjusted for the HRA dimension and organizational performance. The five-point Likert scale ranges from strongly disagree (1) to strongly agree (5) was applied based on previous studies [43]. The five employee engagement analytics items were adapted from [44]. The talent acquisition analytics dimension was measured using five questions adapted from [45]. The manpower planning analytics dimension consisted of five components altered from [46], [47]. Organizational performance was examined via five items adapted from [48], [49].

2.4. Ethical considerations

The collection of research data from human participants is governed by long-established ethical principles. The study described herein was registered prior to data collection with the University of Jeddah's Bioethics Committee of Scientific and Medical Research (HAP-02-J-094). Participants in the study were given an overview of the study, including its objectives, and an assurance of confidentiality. Participants were informed the voluntary nature of their participation and their right to withdraw at any time without penalty or consequences. Participation in the study was completely voluntary. The survey was administered and completed anonymously online to ensure the anonymity and confidentiality of participants' answers. Because the survey was conducted online, obtaining signed written consent was not required. Completion and submission of the anonymous online survey were strictly voluntary and served as informed consent to participate. This approach has been applied in previous anonymous online-survey research [50] and is consistent with established ethical principles for voluntary informed participation [51]. Similar methodological guidance recognizes online-survey consent when participants are informed about the study purpose, confidentiality, voluntariness, and their right not to participate [52].

2.5. Data analysis

Data analysis was conducted using IBM SPSS Statistics version 26.0. Measurement scale quality and the reliability of the data collected prior to hypothesis testing were evaluated. A first evaluation consisted of assessing internal consistency through the application of Cronbach's alpha; secondly, a further evaluation at the item level concerned assessment of the consistency of each item with respect to the total scores (i.e., item–total correlations). Furthermore, the Fornell–Larcker criterion was used to evaluate discriminant validity. Descriptive statistics were employed to offer summary overviews of the research variables and demographic characteristics of the sample. Next, Pearson correlation analyses were carried out to investigate associations between the study variables. Finally, multiple regression analysis was conducted to assess the suggested connections between employee engagement, talent acquisition analytics, manpower planning analytics, and organizational performance.

Since every questionnaire item was required for survey completion, there were no missing values present within the dataset. To determine whether the distributions of the study variables were approximately normal, skewness and kurtosis were evaluated. As stated in [53], skewness values in the range of −2 to +2 and kurtosis values between −3 and +3 suggest an approximately normal distribution. As indicated in Table 1, skewness varied between −0.287 and −0.172, while kurtosis ranged from 0.152 to 0.431, staying within the acceptable limits. The regression assumptions were additionally evaluated through tolerance and variance inflation factor (VIF) values, the Durbin–Watson statistic, and diagnostics of standardized residuals.

Table 1. Skewness and kurtosis

Constructs	Skewness	Kurtosis
Employee engagement analytics	−0.267	0.158
Talent acquisition analytics	−0.216	0.228
Manpower planning analytics	−0.172	0.152
Organizational Performance	−0.287	0.431

2.6. Multicollinearity

Multicollinearity arises when independent variables exhibit a strong correlation with one another, potentially impacting the reliability of regression estimates [54]. It was evaluated through tolerance and VIF metrics. As indicated in Table 2, tolerance values varied between 0.506 and 0.542, surpassing the suggested minimum of 0.10, whereas VIF values ranged from 1.845 to 1.977, staying beneath the limit of 5 [55]. These findings suggest that significant multicollinearity was not present among the independent variables.

Table 2. Variance inflation factor (VIF) test of multicollinearity

Independent variables	Tolerance	VIF
Employee engagement analytics	0.542	1.845
Talent acquisition analytics	0.506	1.977
Manpower planning analytics	0.535	1.871

2.7. Reliability and validity of measures

The scales' reliability and item-level measurement quality were evaluated through Cronbach's alpha and item-total correlations, as shown in Table 3. Employee engagement analytics showed satisfactory internal consistency, with a Cronbach's alpha of 0.750 and item–total correlations between 0.638 and 0.684. Talent acquisition analytics showed sufficient reliability, with a Cronbach's alpha of 0.703 and item–total correlations between 0.582 and 0.715. Manpower planning analytics showed the greatest reliability, exhibiting a Cronbach's alpha of 0.779 and item–total correlations between 0.447 and 0.665. Organizational performance showed adequate reliability, with a Cronbach's alpha of 0.767 and item–total correlations between 0.610 and 0.704. Consequently, every Cronbach's alpha coefficient was above 0.70, and all item–total correlations were greater than 0.30, indicating the scales' internal consistency and the quality of item-level measurement [43].

Table 3. Reliability and validity of measurements

Constructs	Items	Item–Total Correlation	Cronbach's Alpha
	EE_1	0.661	
	EE_2	0.684	
Employee engagement analytics	EE_3	0.664	0.750
	EE_4	0.651	
	EE_5	0.638	
	TA_1	0.582	
	TA_2	0.707	
Talent acquisition analytics	TA_3	0.715	0.703
	TA_4	0.621	
	TA_5	0.696	
	MP_1	0.447	
	MP_2	0.642	
Manpower planning analytics	MP_3	0.664	0.779
	MP_4	0.665	
	MP_5	0.629	
	OP_1	0.610	
	OP_2	0.693	
Organizational Performance	OP_3	0.704	0.767
	OP_4	0.639	
	OP_5	0.629	

2.7.1. Discriminant validity

Discriminant validity was evaluated through the Fornell–Larcker criterion by comparing the square root of the average variance extracted (AVE) for every construct against its correlations with the other constructs. The square roots of AVE for employee engagement analytics, talent acquisition analytics, manpower planning analytics, and organizational performance were .660, .668, .620, and .657, respectively. Although the Fornell–Larcker standard was met across most construct comparisons, there was one exception, as outlined in Table 6. Specifically, the correlation between talent acquisition analytics and manpower planning analytics ($r = .631$) marginally exceeded the square root of AVE for manpower planning analytics (.620). Therefore, the results provide generally supportive, although not complete, evidence of discriminant validity among the four constructs examined here, with limited overlap between talent acquisition analytics and manpower planning analytics.

2.8. Common method bias

The potential for common method bias was assessed using Harman's single-factor test according to the guidelines outlined by [56]. The initial factor accounted for 28.84% of the overall variance; nonetheless, it is typically regarded that common method bias could be an issue if one factor captures over 50% of the total variance. As the initial factor did not account for most of the variance, common method bias was probably not a significant issue.

3. Results

3.1. Participants characteristics

Table 4 offers a summary of the participants' demographic features. Females comprised the larger proportion of the sample (n = 190; 67.6%), compared with males (n = 91; 32.4%). The largest age category consisted of participants aged 30–35 years (n = 151; 53.7%), followed by those aged 36–40 years (n = 65; 23.1%), those under 30 years (n = 48; 17.2%), and those over 40 years (n = 17; 6.0%). Regarding job roles, employees represented the largest group (n = 135; 48.0%), followed by heads of department (n = 76; 27.0%), managers (n = 45; 16.0%), and other positions (n = 25; 9.0%). In terms of experience, most participants had 1–5 years (n = 102; 36.3%) or 6–10 years (n = 91; 32.4%) of experience, followed by 11–15 years (n = 74; 26.3%) and more than 15 years (n = 14; 5.0%).

Table 4. Participant's characteristics

Variables	Characteristics	N	Percentage
Gender	Male	91	32.4
	Female	190	67.6
Age	Under 30 years old	48	17.2
	30–35 years old	151	53.7
	36–40 years old	65	23.1
	Over 40 years old	17	6.0
Job title	Employee	135	48.0
	Manager	45	16.0
	Head of Department	76	27.0
	Other	25	9.0
Years of experience	1–5 years	102	36.3
	6–10 years	91	32.4
	11–15 years	74	26.3
	More than 15 years	14	5.0

3.2. Descriptive statistics

Table 5 exhibits descriptive statistics for the variables of the study. The mean scores for the variables, evaluated using a five-point Likert scale, ranged from 3.220 to 3.277, indicating that most respondents moderately agreed with each item. Manpower planning analytics had the highest mean (M = 3.277, SD = 0.652), while organizational performance (M = 3.264, SD = 0.685) ranked second. Employee engagement analytics (M = 3.237, SD = 0.712) ranked third. Talent acquisition analytics had the lowest mean (M = 3.220, SD = 0.709). All of the standard deviations (from 0.652 to 0.712) were relatively low, indicating that respondents tended to answer the questions similarly.

Table 5. Descriptive statistics

Constructs	Mean	SD
Employee engagement analytics	3.237	0.712
Talent acquisition analytics	3.220	0.709
Manpower planning analytics	3.277	0.652
Organizational performance	3.264	0.685

3.3. Correlation matrix

Table 6 presents the correlations among the study constructs together with the Fornell–Larcker discriminant validity assessment. Employee engagement analytics was positively and significantly associated with talent acquisition analytics ($r = 0.625$, $p < .01$) and manpower planning analytics ($r = 0.596$, $p < .01$). Talent acquisition analytics was also positively associated with manpower planning analytics ($r = 0.631$, $p < .01$). Organizational performance was positively and significantly associated with employee engagement analytics ($r = 0.521$, $p < .01$), talent acquisition analytics ($r = 0.527$, $p < .01$), and manpower planning analytics ($r = 0.546$, $p < .01$). These results indicate moderate positive associations between each HR analytics dimension and organizational performance. The diagonal values in Table 6 correspond to the square roots of AVE and indicate generally adequate discriminant separation, with the marginal exception of talent acquisition analytics and manpower planning analytics.

Table 6. Correlation matrix and Fornell–Larcker discriminant validity assessment

Constructs	Employee engagement analytics	Talent acquisition analytics	Manpower planning analytics	Organizational performance
Employee engagement analytics	0.660			
Talent acquisition analytics	0.625**	0.668		
Manpower planning analytics	0.596**	0.631**	0.620	
Organizational performance	0.521**	0.527**	0.546**	0.657

Note. Bold diagonal entries indicate the square root of the AVE. Off-diagonal entries represent Pearson correlations. ** The correlation is significant at the 0.01 level.

3.4. Hypothesis test

A multiple regression analysis was executed to investigate the associations of employee engagement analytics, talent acquisition analytics, and manpower planning analytics with organizational performance (Table 7). The overall the regression model showed statistical significance, $F(3, 277) = 56.55$, $p < .001$, and explained 38.0% of the variance in organizational performance ($R^2 = 0.380$; adjusted $R^2 = 0.373$). Employee engagement analytics was positively associated with organizational performance ($B = 0.214$, $SE = 0.062$, $\beta = 0.222$, $t = 3.460$, $p = .001$), supporting H1. Talent acquisition analytics demonstrated a positive relationship with organizational performance ($B = 0.204$, $SE = 0.064$, $\beta = 0.211$, $t = 3.175$, $p = .002$), supporting H2. Manpower planning analytics showed the strongest positive association with organizational performance ($B = 0.294$, $SE = 0.068$, $\beta = 0.280$, $t = 4.323$, $p = .001$), supporting H3. Thus, all three hypotheses were supported in terms of statistically significant positive associations with organizational performance.

Regression diagnostics provided additional support for the model. The Durbin–Watson statistic was 2.064, indicating no meaningful residual autocorrelation. Inspection of standardized residuals against predicted values did not show a pronounced systematic or funnel-shaped pattern, indicating that the residual diagnostics were reasonably consistent with the assumptions of linearity and constant variance.

Table 7. Multiple regression analysis

Predictor	B	SE	β	t	p
(Constant)	0.953	0.181	—	5.269	< .001
Employee engagement analytics	0.214	0.062	0.222	3.46	.001
Talent acquisition analytics	0.204	0.064	0.211	3.175	.002
Manpower planning analytics	0.294	0.068	0.280	4.323	.001

Note. $R = 0.616$, $R^2 = 0.380$, Adjusted $R^2 = 0.373$, $F(3, 277) = 56.55$, $p < 0.001$; Durbin–Watson = 2.064.

4. Discussion

This research examined the connection between HRA and organizational performance through three kinds of HR analytics in Saudi Arabia: employee engagement analytics, talent acquisition analytics, and manpower planning analytics. All three forms of analytics had significant positive associations with organizational performance. Manpower planning analytics was the most strongly associated form of HR analytics with organizational performance. The observational data from this research supports the strategic importance of HR analytics in Saudi organizations. The empirical evidence also supports prior research that found a positive association between analytics-based HR functions and organizational performance.

Employee engagement analytics has been shown in previous research to be positively related to organizational performance because it provides firms with the ability to analyze employees' productivity, absenteeism, engagement, and organizational commitment [1]. In the context of Saudi Arabia, the connection between employee engagement and organizational performance is important for achieving the national priorities identified within Vision 2030 for workforce participation and efficiency. According to the RBV, employee engagement analytics can provide an organization with a systematic way to manage its human capital by providing firms with better decision-making capabilities through the utilization of workforce data [7].

The positive association between talent acquisition analytics and organizational performance supports prior research on the use of analytical data for recruitment and selection processes [6], [28]. Using analytical processes to inform talent acquisition provides organizations with systematic information about recruitment channels, candidate profiles, and workforce needs. Therefore, the results from this study support the idea that talent acquisition analytics represents both an operational process (i.e., how organizations recruit employees) and a strategic capability that enables organizations to effectively utilize their human capital to meet business goals.

Manpower planning analytics provided the highest standardized coefficient among the three dimensions of HR analytics. These findings are similar to those of other recent studies that have emphasized predictive workforce planning, forecasting, and the use of analytics to strategically allocate human resources [9], [12]. Manpower planning analytics may be especially important for organizations in Saudi Arabia since they need to adapt to new workforce demands created through economic transformation and meet Saudization objectives [36]. Manpower planning analytics can help organizations make more deliberate decisions regarding how to allocate current workforce capabilities and forecast the future availability of such capabilities. In this sense, these analytics highlight the strategic importance of manpower planning analytics; however, because of the cross-sectional nature of this study, the findings should be interpreted in terms of association rather than causality.

5. Conclusion

This study examined the relationships between employee engagement analytics, talent acquisition analytics, manpower planning analytics, and organizational performance in Saudi Arabian organizations. The findings demonstrate the relevance of HR analytics as a data-informed approach to workforce decision-making within an economic environment undergoing substantial transformation under Vision 2030. The complete regression model was statistically meaningful and accounted for 38.0% of the variance in organizational performance. All three HR analytics dimensions were positively and significantly associated with organizational performance. Manpower planning analytics showed the largest standardized coefficient ($\beta = 0.280$), followed by employee engagement analytics ($\beta = 0.222$) and talent acquisition analytics ($\beta = 0.211$). These results support all three hypotheses while indicating statistical associations rather than causal effects.

5.1. Theoretical contributions

The research enhances the HRA body of literature by demonstrating how employee engagement analytics, talent acquisition analytics, and manpower planning analytics relate to organizational performance rather than treating

HRA as one overarching concept. The research also extends the application of the RBV and human capital theory. According to the RBV, the ability to transform workforce information into strategically useful knowledge is an organizational capability that HR analytics embodies. In accordance with human capital theory, the three analytics dimensions represent the engagement, acquisition, and allocation of human resources. Therefore, the results provide empirical support for using the two theories complementarily in relation to HR analytics in the context of Saudi Arabia.

5.2. Managerial implications

The results provide a basis for real-world managerial decisions to improve the use of data in informing HR decisions. For example, the fact that manpower planning analytics, including forecasting and identifying potential skill deficits, showed a comparatively stronger association with organizational performance than employee engagement analytics and talent acquisition analytics indicates that organizations should consider utilizing this type of analytics when developing their strategic HR plans. Organizations in Saudi Arabia can therefore utilize the analytical tools identified in the research to inform their overall HR strategy and, instead of continuing to rely heavily on intuition when making HR-related decisions, make more informed, data-driven decisions, especially as Saudi organizations continue to develop their workforces in line with Vision 2030.

5.3. Limitations and future research directions

Several constraints need to be considered when analyzing the outcomes. First, due to the nature of this being a cross-sectional study, it is not feasible to draw causal conclusions based on the data collected. Rather than indicating cause-and-effect relationships, the findings identify statistical associations. Second, although the model accounted for a moderate share of the variance in organizational performance, with additional elements like organizational culture and leadership, are also likely to be relevant. Third, the sample comprised only Saudi Arabian organizations, and therefore the generalizability of these results to organizations in other countries is limited. Finally, in addition to the limited overlap identified between talent acquisition analytics and manpower planning analytics, future researchers might wish to use longitudinal rather than cross-sectional research designs to examine temporal relationships. Researchers might also wish to investigate potential mediators or moderators of those relationships, improve the precision of measures for closely related constructs in HR analytics, and assess the role of other organizational characteristics that may explain additional variance in organizational performance. Comparative studies across industries or national contexts would provide evidence about whether similar empirical patterns exist within different institutional and labor-market environments.

Declaration of competing interest

The author states that there are no recognized financial or non-financial competing interests related to any content addressed in this paper.

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Ethical approval statement

Research ethics approval was obtained by the Bioethics Committee of Scientific and Medical Research of the University of Jeddah before data collection (Registration Number: HAP-02-J-094; Application Number: UJ-REC-387).

Informed consent

Consent to participate was acquired via the voluntary completion and submission of the anonymous online survey by the participants.

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