Examining the moderating role of data literacy in the relationship between human resource analytics and employee innovative behavior

Ahmad Nasser Abuzaid[a*]

[a]Mutah University, School of Business, Business Administration Department, Karak, Jordan

CHRONICLE	ABSTRACT
	The practical application of business data analytics in human resource (HR) management activities is still limited and underutilized. The primary reason for this is the requirement for more analytical skills, which can be acquired through data literacy. These skills are necessary to ensure obtaining the potential benefits of human resource analytics linked to desired positive employee outcomes, such as fostering innovative behavior. To address this issue, this quantitative study has been conducted to delve into the prospective moderating role of data literacy in the interaction between human resource analytics and employees' innovative behavior. The core objective of this study is to examine whether human resource professionals' data literacy level significantly impacts the correlation between human resource analytics and the inclination of employees towards innovative behavior. A sample of 250 HR specialists from large companies in Jordan has been used to address this inquiry. A correlational-predictive design has been used in this study. Regression analysis using the SPSS macro-PROCESS software has been utilized to address the study hypotheses. The study reveals a positive connection between HR analytics and employees' innovative behavior. Moreover, it uncovers a noteworthy moderating influence of data literacy on this association. These findings suggest that heightened data analysis proficiency among HR professionals amplifies the potential benefits derived from analytics, thereby enhancing employees' innovative capabilities. As a result, the research suggests that companies upgrade their technical infrastructure for HR functions and concurrently utilize data analytics for informed HR decisions. Further, these insights do serve as necessary inputs in understanding HR analytics and their implications for prudent business strategy. In view of this dynamic nature of HR analytics, the contributions made by the study are immensely valuable; hence, further exploration is needed to fill in gaps within existing knowledge.

1. Introduction

Dynamic market shifts and changing technology require risky and traditional structures to alter operations. In the modern business world, innovation has become a survival strategy that is necessary for organizations to endure and prosper (Putra & Pramusiwi, 2023). Activating human capital within organizations forms an important channel through which innovation can be pursued. The basis of this assertion lies in the fact that innovative workplace behaviors exhibited by employees have the potential to drive organizational innovation, leading to business success.

Empirical research shows that innovative work behavior of employees leads to the production of new products and services that improve operational efficiencies and productivity, as well as enhance competitive edge (Jahangir et al., 2023). Furthermore, such a propensity for innovation positively correlates with customer satisfaction levels regarding products and services (Retkutė and Davidavičienė, 2021). This insight arises from understanding customers' wants and providing exact solutions

for those requirements (Putra & Pramusiwi, 2023). Moreover, adopting innovative behaviors also brings positive effects on the work environment. Employees who adopt innovation actively contribute to refining processes, procedures, and technologies, enhancing working conditions and employee well-being (Purwanto et al., 2022). In turn, this brings about a higher involvement and satisfaction in employment. All this enthusiasm and motivation created by the culture translate into hard work with increased productivity (Sueb & Sopiah, 2023).

Employees' adeptness at innovative behavior is pivotal in generating new ideas across various domains such as products, services, technology utilization, and work methodologies (De Jong & Den Hartog, 2008). This dynamic behavior directly affects organizational performance, thus significantly contributing to overall success (Purwanto et al., 2022; Vandavasi et al., 2020). Therefore, to realize tangible achievement, organizations should take the sole responsibility to nurture and promote innovative behavior among their employees. Human resource (HR) practitioners understand that it is critical to build such conduct in their organizations, as positive results are linked with employees' innovative behavior. As a result, organizations continuously promote or encourage such behavior by HR practitioners using modern approaches like Human Resource Analytics.

Human resource analytics has gained substantial prominence lately owing to the profuse information concerning employees' availability (Cho et al., 2023). Data obtained from employees is crucial in understanding the employees' behaviors, output, and satisfaction, among other aspects, which are essential in talent decisions to operate in the competitive business environment (Álvarez-Gutiérrez et al., 2022). Human resource analysis is beneficial for talent attraction, payment strategy designs, and identification of other opportunities for employee development, among other things (Uma et al., 2023). In addition to these, human resource analysis enables companies to grasp their staff's ever-evolving demands and make relevant changes to HR, creating individualized and flexible working environments (Qamar & Samad, 2022). These analyses can precisely identify the elements influencing employees' efforts to explore and adopt new ideas, promoting innovative organizational behavior. These elements may include the efforts of their managers and colleagues and the presence of fundamental resources (Cho et al., 2023; Coulthart & Ryan, 2022). Training programs tailored to boost innovative ideas and motivation can be developed as businesses capitalize on this information. This promotes a culture of creative thinking and develops the necessary abilities to tap into the staff's innovative ideas power (Marler & Boudreau, 2017). This makes it possible for businesses to make knowledgeable decisions about the behaviors they want to encourage, such as innovative work practices, creating an optimum environment, and workforce performance (Koo & Fallon, 2017; Levenson, 2005).

To effectively implement analytics in human resources, HR professionals should be well versed in their data capabilities, which include the skills and expertise to work with data, present and analyze results, and report findings (Angrave et al., 2016; Ulrich et al., 2017). When this feature is maximally developed, HR specialists can unlock all the analytics' possibilities to impact decisions and enable them to make the best choices relevant to their business goals. The outcomes are often increased efficiency, boosted organizational performance, and a more concerted and competitive effort on a global scale (McCartney et al., 2020).

Given the identified gaps in the literature reviewed above, this study is necessary to fill the knowledge gap and determine the impact of HR analytics on employee outcomes and behaviors, particularly in terms of innovation behavior. Moreover, the objective is to showcase how HR analytics impact actions such as innovation, implicitly confirming their role in enhancing productivity. In this pursuit, incorporating employee actions within HR analytics enhances the existing literature and provides significant value to the field. Additionally, there is a clear requirement for empirical approaches to grasp HR analytics, along with an investigation into the moderating influence played by the skills and competencies of HR professionals. To comprehensively address these gaps, the present study empirically evaluates how HR experts' data literacy affects the connection between HR analytics and employee innovative behavior. This evaluation utilizes a sample of HR experts from prominent companies in Jordan. In more precise terms, the study aims to achieve the following objectives:

1. To comprehend the correlation between data analytics and employees' innovative behavior and, if supported, to specify the nature of this correlation.

2. To examine whether HR professionals' data literacy moderates the connection between data analytics and employees' innovative behavior and to pinpoint differences in this connection based on varying levels of HR professionals' data literacy.

This research holds significant importance and worth due to its precise examination of the interplay between the mentioned variables. Doing so sheds light on aspects that prior studies have often overlooked. Furthermore, it enriches the domain of HR analytics with fresh empirical insights. As a result, this effort contributes to deepening the comprehension of the intricate dynamics inherent in these variables, thereby advancing the field of HR analytics.

2. Literature review and hypotheses development

2.1 Human Resource Analytics (HRA)

The application of analytics in managing human resources has been in practice for several years. Jac Fitz-enz, a pioneer in this field, authored the first book titled "How to Measure Human Resource Management" in 1984 (Fitz-enz, 1984). After that, HR analytics has developed, especially within the recent digital era, and its importance has grown in organizations.

Scholars sometimes use interchangeable or alternative terms when referring to HR analytics, such as "people analytics," "talent management analytics," "human capital analytics," "workforce analytics," and "algorithm-based HR decision-making." Therefore, the interpretation of the term HR analytics initially evoked debates, and there are many opinions on this issue since "HR analytics means different things to different people" (Bassi, 2011). For some, HR analytics measures HR metrics and should include hiring, turnover, and compensation (Jain and Jain, 2020). They discuss the need to "measure" one's performance against the performance of one's peers. However, the opposite view is that such "measurements" do not imply a position of HR analytics (Fitz-Enz, 2010). However, within the framework of other studies (e.g., Mohammed, 2019; Molefe, 2013; Mishra et al., 2016), HR analytics appears to be a more sophisticated and advanced tool. Scholars assert that human resource analytics entails applying statistical techniques, algorithms, and research designs to assess employee data, resulting in actionable reports (Levenson, 2005). Its primary objective is to extract valuable insights from personnel data, facilitating the anticipation of behavioral patterns, training expenses, turnover rates, and individual contributions (Marler and Boudreau, 2017). This methodology, called predictive analysis, epitomizes a contemporary approach to HR management (Andersen, 2017). Davenport et al. (2010) have contributed to clarifying certain aspects in the context of these deliberations. They posit an encompassing perspective containing the various facets of "talent analytics." From this vantage point, HR analytics spans a broad spectrum, encompassing human capital management and implementing intricate analytics geared towards optimizing the "talent supply chain" (Davenport et al., 2010). Another line of thought asserts that HR analytics embodies an orientation toward evidence-based management (Pfeffer & Sutton, 2006; Marler & Boudreau, 2017).

Various researchers define HR analytics differently within the context of management and organization. As per Bassi (2011), HR analytics refers to using evidence-based methods to make informed decisions regarding the human resources aspect of a business. This valuable tool enables better decision-making about the people's side of a business. HR analytics employs a range of instruments and technologies, from simple HR metric reporting to advanced predictive modeling. Mondare et al. (2011) define HR analytics as a tool that connects people with critical business outcomes. They emphasize the importance of linking HR analytics with strategic HRM to effectively demonstrate the direct impact of human resources on business performance. Koo and Fallon (2017) argue that HR analytics is a technique that assists organizations in achieving their strategic objectives by utilizing research based on HR-related evidence. This technique aims to identify and quantify the drivers of business outcomes related to people to make better decisions that can enhance HR practices and organizational performance. Marler and Boudreau (2017) describe HR analytics as an HR technique that utilizes IT to conduct mathematical, statistical, optical, and descriptive analyses linking HR procedures with organizational outcomes to facilitate decision-making based on data.

From the above discussion, HR analytics represents an evidence-based approach that utilizes data to empower management to make more informed decisions regarding organizational personnel by employing technologies that generate simple reporting or HR metrics and enable using predictive modeling.

Watson (2010) categorizes HR analytics into descriptive, predictive, and optimization. The first level of analysis, descriptive analytics, interprets past actions, historical data, and outcomes (Koo & Fallon, 2017). Predictive analytics, in contrast, anticipates future behavior based on previous data (Fernandez and Gallardo-Gallardo, 2020). Optimization analytics achieves optimal results through simultaneous linear programming (Makarius et al., 2020).

2.1 Data Literacy

The ability to understand and utilize data effectively in decision-making is called data literacy, which involves various skills and knowledge. These include identifying, collecting, organizing, analyzing, summarizing, prioritizing data, creating hypotheses, recognizing issues, and acting, as highlighted by Wolff et al. (2016).

Data literacy is the ability to comprehend and use data in decision-making fully and involves various skills and knowledge. According to Wolff et al. (2016), data literacy includes identifying data, collecting, organizing, analyzing, and summarizing, prioritizing, developing hypotheses, recognizing issues, and acting. Deahl (2014) defines data literacy in organizational settings as the ability to understand, find, gather, explain, present, and back up arguments using qualitative and quantitative data. It also includes understanding the fundamentals of secondary research. Another definition by Vahey et al. (2006) includes integrating data into evident-based reasoning, creating, and responding to inquiries using related data, tools, and illustrations, analyzing information from data, forming and examining data-derived findings and justifications, and using data to address real-world issues and communicate plans. Data literacy is also based on knowledge of the production and reuse process, understanding the value, types, and formats of source data, and the availability of appropriate data sources for informational needs according to Kodrat et al. (2024) and Wolff et al. (2016), data literacy also involves evaluating data and sources, research methodologies, synthesizing and selecting data, combining it with previous knowledge, media, and other sources, and presenting quantities such as data, tables, and graphs in reports (Gummer & Mandinach, 2015). Moreover, data literacy includes using data ethically and applying the results of data analysis to learning, decision-making, or problem-solving. It also requires planning, organizing, and self-assessing throughout the entire data analysis process, as Shields (2005) emphasized.

Big data analytics, including HR analytics, perceived data literacy as the comprehension, addressing, scrutiny, and persuasion of data (Sander, 2020). It implies understanding what data conveys and what sections of the world it expresses. It involves constructing, acquiring, refining, and administering data. Moreover, data literacy includes filtering, processing, summarizing,

and juxtaposing data with different analytical tasks (François & Monteiro, 2018). Data literacy implies using data to support a bigger story and convey a specific message to a particular audience (Sander, 2020). The HR experts have already realized the importance of data literacy as a fundamental skill to a successful application and have already realized the importance of data literacy as an essential learned skill in HR analytics (Bassi, 2011). It is necessary to have a good knowledge of IT to leverage analytic software tools and ultimately interpret organizational measures (Angrave et al., 2016).

Many research papers indicated that abstinence from HR analytics with suitable analytical abilities may result in misinterpretations and misspecification, generating ignored opportunities and detrimental influences on the employees and the many things they perform (e.g., Vaiman et al., 2021; Boudreau & Lawler, 2012). Therefore, data literacy is needed to use HR analytics and support the argument that HR is irrelevant in real business today. By gaining this knowledge and making better-informed determinations, HR practitioners can improve their efficiency and accomplish it more productively.

2.2 Employees Innovative Behavior

The employee's innovativeness refers to "the intention to generate and develop new and valuable ideas for products, services, or work processes, followed by the necessary individual-level actions, such as designing, introducing, and implementing those ideas" (De Jong & Den Hartog, 2008). Innovativeness also indicates an employee's willingness to promote and explore innovative ideas and requires help implementing them (Singh & Sarkar, 2012). Employee innovative behavior is defined as the employee's action to generate new ideas to implement within his working role, group, or organization to improve his role performance (Vandavasi et al., 2020). This phenomenon is a multi-stage process that entails problem identification, idea generation, and resolving the identified problem. Moreover, the attainment of support from the workforce is essential (Afsar et al., 2014). In essence, innovative behavior represents a dynamic process through which employees generate, create, develop, apply, enhance, realize, and modify novel ideas in pursuit of improved performance within the organizational context (Sueb & Sopiah, 2023).

Numerous studies have indicated that employees' innovative behavior involves four fundamental aspects. The first aspect is exploring opportunities, which is a behavior that reveals new opportunities by identifying an event or problem that needs a solution. The second aspect is generating ideas, which involves creating new ideas or concepts to solve problems or improve work performance for development. The third aspect is defending ideas, which refers to enthusiastic behavior involving implementing and applying ideas at work. The fourth and final aspect is the application of concepts, which involves using and reforming products or procedures and acting to develop, examine, and promote innovative ideas (De Jong & Den Hartog, 2008; Purwanto et al., 2022).

Recent studies have further confirmed that employees' innovative behavior is the total individual behavior that lies in the emergence, presentation, and implementation of new and profitable things. The act of innovating involves creating a fresh product or technology, altering administrative processes to enhance work connections, and integrating new concepts and technology to boost the productivity and effectiveness of work output (Purwanto et al., 2022). It is crucial to understand that innovation has comprised of two stages. The first stage is the creativity phase, where one determines the problem and personally provides solutions. The next stage is the implementation phase, which involves implementing inventive ideas or solutions within the enterprise (Messmann & Mulder, 2012).

Hypotheses Development

The significance of HR data analysis in ensuring that a company achieves its success is very significant. HR data analysis helps enhance HR operations, thereby creating chances for quality improvement, resulting in high employee efficiency and output (Ameer et al., 2023). The extensive insight into the significant influence of HR data analysis should increase concerns in academic circles (Boudreau & Lawler, 2012; Vaiman et al., 2021). This emphasis is driven by the need to make sure that due to the lack of a sound understanding of HR data analytics, one does not make mistakes by simply believing that it is a good process.

HR analytics has already been measured in several studies, including the work by Cho et al. (2023), which confirmed that organizations should further encourage and support effective collaboration between managers and employees, creating new and better practices. Another study by Madhani (2023) argues that HR analytics can also help to identify individuals "who are/ can demonstrate innovative behaviors that create significant value for" the company and guide them to keep their innovative jobs. Finally, Nicolás-Agustín et al.'s (2022) work claims that staff who trust HR analytics are more likely to produce and implement new ideas at work. The latter is also confirmed by the work of Noopur and Dhar (2020), who establish that knowledge-related HR practices positively contribute to employee creativity. However, there are other counter-leading factors. For instance, Singh and El-Kassar (2019) warn that the benefits of HR analytics depend on how employees perceive them and determine whether to stay aligned with the organizational objectives and a willingness to share information and be innovative. Based on Boudreau and Jesuthasan (2011), HR analytics can identify employees with impressive innovative behavior attributes and thus allow organizations to encourage and support these individuals further.

However, as prior research notes, strong analytical skills help the responsible personnel in human resources develop personnel, which enables them to find out the weaknesses and strengths of personnel. Thus, professionals can create customized programs and tactics to improve employees' work, such as stimulating innovation (Ulrich et al., 2017; Gupta et al., 2020). Secondly, the study by Gupta et al. (2020) shows that HR analytics professionalism allows efficient oversight of the assessment of

employees. In particular, professionals with such a specialization actively stimulate employees to launch innovative activities via democratic approval of their proposals and guiding them. Moreover, they resolve the issue of the objectivity of assessment by establishing objectives and offering transparent feedback regarding the latter, which can enhance innovative activity. Thirdly, Minbaeva (2018) emphasizes that HR professionals must possess the necessary analytical skills to analyze HR analytics data. This competence helps to make it easier to prompt individuals to suggest innovative proposals that create significant value for the enterprise.

Cutting-edge technology in contemporary enterprises has allowed vast personnel information to be collected from multiple origins. This is a significant contribution towards understanding employee behavioral patterns, identifying the skills known to employees, and establishing areas with gaps that need attention and improvement (Coulthart & Ryan, 2022). With the mentioned capabilities, the business organization can improve efficiency and workforce performance, ultimately bolstering its competitiveness and performance (Koo & Fallon, 2017). However, to make the best of the available data, an understanding of the mathematical and statistical primitives, the contemporary tools available, and data-related methods of approach are required, all of which form part of data literacy (Sander, 2020). Data literacy is essential in understanding valuable insights from the collected data, which would further empower business organizations to develop viable strategies and programs for different aspects of the business and develop data-driven systems (D'Ignazio & Bhargava, 2015). It is also helpful in helping organizations ascertain the reliability of the data collected and its alignment with the company's objectives to operationalize it (Shields, 2005). For example, suppose an enterprise wishes to cultivate innovative behavior among its employees. In that case, the data can only be helpful if correctly interpreted using a suitable analysis of the business's objectives. It is, thus, a helpful analysis method for developing a corresponding program to create a supportive environment (Wolff et al., 2016). Therefore, the data literacy approach significantly magnifies HR analytics' benefits from the perspective of a business organization. The study's hypotheses can thus be expressed as follows:

H₁: *HR analytics positively affects employees' innovative work behavior.*

H₂: *Data literacy moderates the relationship between human resource analytics and employees' innovative work behavior.*

3. Methodology and procedures

3.1 Method and design

The study utilized a quantitative research methodology with a deductive approach to validate hypotheses based on theoretical constructs related to the research topic (Barczak, 2015). The study was correlational-predictive, highlighting the relationship or association between two or more variables (Kerlinger & Lee, 2000). This design was deemed suitable for the study as measuring variables or data numerically and objectively is the primary focus of quantitative approaches, which utilize statistical techniques to analyze relationships and patterns between them. Additionally, these approaches draw conclusions from statistically tested data and infer insights that can be generalized to a larger population.

3.2 Population and Sample selection

The target population was human resource specialists working in large corporations in Jordan. Determining the sample size in this study involved utilizing nonprobability convenience sampling, whereby individual human resource specialists willingly participated in the survey. A minimum sample size of 200 was calculated using the G*Power software to validate the study's hypotheses. In the initial assumption, a basic linear regression analysis was carried out with one predictor, and a priori computation was done. With an alpha level of 0.05, a power of 0.8, and a medium effect size of $f2=0.15$, it was determined that a minimum of 150 participants would be needed for the study.

Similarly, an a priori calculation was conducted for the following assumption, where three predictors were included, and the calculation required multiple linear regression. Given the above section with the same alpha level, effect size, and power, at least 200 participants will be required for the study. However, there will be some missing data, and to capture these gaps and strengthen the analysis, the researcher expanded the number of participants to 250. This will allow for more missing information and help meet the recommended minimum requirements. This yielded 250 as the appropriate sample size for this research methodology to ensure strong statistical power and sound inferences. Once the sample size was acquired, potential participants were sent an email comprising an invitation letter, in which objectives were elaborated and participation's importance highlighted. A guide on filling out the questionnaire was provided. Participants were given a two-week window to submit. The current study consisted of 40% females and 60% males; their experience elapsed 10-15 years, 55% had a bachelor's degree, and their ages varied from 40-45.

3.3 Measures

The measurement of both human resource analytics that were applied in the current research was conducted based on the scale developed by McCartney and Fu (2022) that built on the previous work of Minbaeva (2018), Pipino et al. (2002), and Ulrich et al. (2017, The innovation of the employees was measured based on the scale designed by Scott and Bruce (1994). In contrast, data literacy was measured based on the work of Aung et al. (2019). The referred measurement tools are valid for measuring the selected factors accurately. A "five-point Likert scale" was used to collect the information regarding all survey questions. The scale included a range from "Strongly Disagree" to "Strongly Agree", which allowed study participants to show their preferences and attitudes. The Likert scale is widely used in research to measure perceptions and attitudes.

4. Data analysis

4.1 Goodness of fit indices, validity, and reliability of the model.

Before testing the study hypotheses, a confirmatory factor analysis was performed to check whether the measurement model of the study variables was appropriate and whether the model fit indices were suitable. The quality of model indicators assessment indicated a good fit for the model and adequate reliability for the measurement purposes. The reliabilities of the model were as follows: $\chi2 = 254.311$, $\chi2 / df = 2.540$, CFI = 0.958, SRMR = 0.056, and RMSEA=0.063 (Hair et al., 2014; Thakkar & Thakkar, 2020). Tables 1 and 2 present the accuracy and dependability of the measurement model. First, the dependability of the loadings was checked, and initially, all the loadings appeared to be acceptable. According to the standards of Hair et al. (2018), satisfactory loads are those with coefficients higher than 0.50.

Second, composite reliability and Cronbach's alpha were used to determine the scale's consistency. As can be seen in Table 3, Cronbach's alpha for HR analytics, data literacy, and employee innovative behavior was 0.912, 0.928, and 0.905, respectively. The three Cronbach's alpha coefficient values are satisfactory, as Hair et al. (2018) established a value greater than 0.7, indicating high consistency in the scales used. The composite reliability of the components is also desirable, with the CR value of all parts being 0.7 or more.

Third, convergent validity was evaluated, which means the extent to which statements focusing on the same dimension or variable work together and can be loaded on one dimension or variable. Finally, the researchers conducted the average variance extracted and ensured that each measured dimension or variable was more than 0.50. The statistical analysis results demonstrated that all AVE values were acceptable, according to Hair et al. (2018).

In addition, the author also calculated the composite reliability and Cronbach's alpha coefficients. The values strongly support internal consistency. The computed data produced Cronbach's alpha coefficient for HR analytics, data literacy, and employee innovative behavior, equaling 0.912, 0.928, and 0.905. All coefficients from previous research were used, and ratings above 0.7 are considered satisfactory. Additionally, the calculated components' composite reliability thus met their criteria, with values higher than 0.70 according to all the required standards. Moreover, convergent validity was considered, which analyses how "well statements associated with a particular dimension or variable load onto a single dimension or variable." Lastly, the author proposed a calculated average variance extracted, with the balance not to be lower than 0.50. Each measured dimension or variable was used with solid support. All AVE values accordingly met the acceptable criteria calculated by the described tests (Hair et al., 2014).

Finally, the author assessed discriminant validity, indicating that each part or factor is distinct. The square root of the average variance was calculated, and the correlations of one factor should always be higher than the rest of the factors. The statistical results showed that all the mentioned values fit the necessary conditions, and the correlation coefficients of squared AVE were higher than each in the same row (Fornell & Larcker, 1981).

Table 1
Factor loading, Cronbach's alpha, Composite Reliability and Convergent Validity.

Variable	Indicator	Loadings	α	CR	AVE
HR analytics	"The HR data we have is correct and reliable"	0.74	0.912	0.913	0.562
	"The HR data we have is sufficiently up to date"	0.78			
	"The HR data we have is presented in the same format"	0.71			
	"The HR data we have is complete, and no necessary data is missing"	0.75			
	"The HR data we have is collected regularly"	0.77			
	"Our HR Department translates data into useful insights"	0.73			
	"Our HR department identifies problems that can be solved with data"	0.70			
	"Our HR Department effectively uses HR analytics to create value for my organization"	0.77			
	"Our HR Department has success stories to justify HR analytics projects"	0.74			
	"Our HR Department inspires relevant organizational stakeholders (e.g., senior management teams and line managers) to take action based on their findings"	0.71			
	"Our organization's stakeholders use the data-driven insights that we provide"	0.78			
Data literacy	"Finding the data."	0.71	0.928	0.929	0.549
	"Evaluating the data quality."	0.75			
	"Interpreting the data in context."	0.79			
	"Presenting the data by appropriate means."	0.74			
	"Taking into account the needs and capacities of reception by the audiences."	0.73			
	"Data visualization."	0.72			
	"Statistical knowledge and skill."	0.78			
Employees innovative Behavior	"Searches out new technologies, processes, techniques, and/or product ideas."	0.70	0.905	0.906	0.581
	"Generates creative ideas."	0.73			
	"Promotes and champions ideas to others."	0.76			
	"Investigates and secures funds needed to implement new ideas."	0.79			
	"Develops adequate plans and schedules for the implementation of new ideas."	0.72			
	"Is innovative."	0.77			

Table 2
Values of athematic mean, standard deviation, and model discriminant validity

Variable	Mean	Standard deviation	HRA	DL	EIB
HRA	3.82	0.619	(0.749)		
DL	3.68	0.774	0.473	(0.740)	
EIB	3.79	0.712	0.598	0.429	(0.762)

4.1 Statistical procedures

The new SPSS tool developed to examine the research hypotheses was used. PROCESS fundamentally differs from Structural Equation Modeling SEM in that it uses honest squares analysis to estimate each equation simultaneously compared to maximum-likelihood estimates MLE, which simultaneously solves all equations. Nevertheless, all variables in the model are factored into the equation simultaneously. While PROCESS substantially differs from SEM, the results of both analyses are comparable, which has made the method a preferred approach applicable in different scientific fields (Hayes, 2018; Hayes & Rockwood, 2010).

The study used multiple regression models to verify its hypotheses. A basic linear regression analysis was applied to tackle H1, whereas a moderator multiple linear regression analysis was employed to tackle H2. The simple regression analysis allowed for assessing the predictive capacity of a single variable about another variable, as Kerlinger and Lee (2000) posited. On the other hand, using multiple linear regression analysis allowed the author to explore how multiple factors can predict another factor, enhancing the study's analytical abilities, as Kerlinger and Lee (2000) described. In relation to H2, which suggested the existence of a moderator factor, the study utilized moderation analysis. This statistical process treated the predictor and moderator as two separate factors in accordance with (Hayes, 2018). A multiple linear regression model was generated to assess the validity of the moderator hypothesis, H2. It is essential to mention that the degree of statistical significance for H1 and H2 was $p < .05$.

Before performing the analysis, eight assumptions necessary for multiple linear regression analysis were thoroughly checked and confirmed. To begin, since the dependent variable, employees' innovative work behavior, was continuous, the conditions for statistical testing were appropriate. As for the two predictor variables, human resources analytics and data literacy were also continuous, allowing for accurate statistical calculations. Afterward, it was also revealed that residuals were independent, which means that there was no bias in the determined results of the statistics. In addition, the relationships between the dependent and predictor variables are linear, which ensures the model is statistical. The data also turned out to be homoscedastic, which means the residual variance is the same across all levels of the predictor variables. There was no multicollinearity because it would have presented itself as a skewed regression line weight of one of the variables on the predictor variable. The data also had no significant outliers, as shown on the residual versus fitted values scatterplot. Finally, the residual on the regression line was normal, showing normal distribution.

After preparation, moderation analysis was run to test both hypotheses 1 and 2 using the PROCESS macro developed by Hayes. The PROCESS add-on for SPSS was used for the analysis, conducting simple linear regression for hypothesis 1 and multiple regression for hypothesis 2. The study was conducted using Model 1 of the PROCESS tool to avoid multicollinearity; all product-defining variables were mean-centered. A probing method with a significance level of p equation 16th, 50th, and 84th percentile was conducted, and whenever a measurement was above or a significant result appeared, Johnson-Neyman output was selected. The above methodological procedures illustrate that the study adhered to the statistical methods when executing the moderation analysis.

4.2 Hypotheses testing

The results of the present study, as demonstrated by the PROCESS output, yielded an R2 value of 0.357. This value signifies that the model can account for a substantial proportion, namely 35.7%, of the variability in employees' innovative work behavior prediction. Furthermore, the statistical analysis presented in Table 3 confirms the model's significance, with a p-value of less than 0.001 and an F-value of 61.25 for the three degrees of freedom and 246 sample size.

Based on the observed statistical significance of the model, it can be inferred that the variables of HR analytics, data literacy, and their interaction (HRA × DL) influence the prediction of employees' innovative work behavior. A graphical representation of this relationship is depicted in Fig. 1.
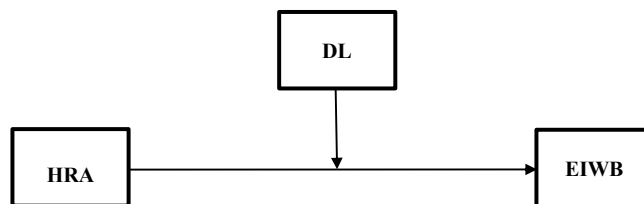
Fig. 1. Conceptual model

Table 3

Model Summary

R	R2	MSE	F	df 1	df 2	P
0.598	0.357	1.05	61.25	3.00	246.00	.0000

Upon closer examination of the association between HRA and EIWB, it is revealed that the statistical analysis shows a significant relationship, with a p-value of .001. This outcome confirms the validity of hypothesis (H1). A significant and positive connection exists between HR analytics and employees' innovative work behavior. To further explore this relationship, a regression model was employed, wherein the coefficient of a predictor variable indicates the extent to which a change in the predictor variable corresponds to a change in the criterion variable (Hayes, 2018). For example, the obtained coefficient value (b1) of 0.194 indicates that a one-unit increase in HRA (X) correlates with a 0.194-unit increase in EIWB (Y). The statistical analysis and 95% confidence intervals about H1 are outlined in Table 4.

Table 4

Simple Regression Coefficients

	Coeff.	Se	T	P	LLCI	ULCI
Constant	4.91	.0530	65.41	0.00	4.98	5.10
HRA	.194	.0405	4.62	0.00	0.27	0.41

* HRA: Human Resource Analytics, the independent variable.

** EIWB: Employees Innovative Work Behavior, the dependent variable.

While testing H1 requires the moderator variable mean-centering, the PROCESS macro only enables the mean-centering of both independent variables. Despite this limitation, Hayes (2018) clarifies that mean-centering does not affect the overall model fit, the interaction, or the interaction coefficient (b3), which is central to H2.

To further visualize the potential effects of the predictor variable (HRA), the moderator variable (DL), and their interaction (HRA×DL) on the criterion variable (EIWB), a statistical diagram, as depicted in Fig. 2, was generated. This diagram serves as an aid in comprehending whether the ability of HR analytics to predict employees' innovative work behavior depends on the data literacy of HR professionals. Variable coefficients, including b1, b2, and b3, presented in the diagram convey the magnitude of change in the criterion variable for each unit change corresponding to the coefficient (Hayes, 2018). Significantly, the coefficient b3 must differ from zero for the relationship between the predictor and criterion variable to depend on the moderator (Hayes, 2018).
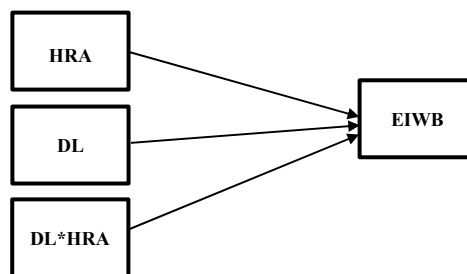

Fig. 2. Statistical model

Table 5 presents the coefficients for the complete regression model, considering the moderation analysis. The statistical analysis shows that the interaction variable, b3, has a coefficient value of 0.092, which differs significantly from zero, with a t-value of 2.94 and a p-value of 0.000. This coefficient's 95% confidence intervals are [0.14, 0.27]. This finding indicates that the moderator variable impacts the predictive association between the predictor and criterion variables.

Table 5

Model regression coefficients

	Coeff	Se	T	P	LLCI	ULCI
Constant	4.91	.0530	65.41	0.00	4.98	5.10
HRA	.194	.0405	4.62	0.00	0.27	0.41
DL	.488	.0438	9.77	0.00	0.39	0.53
Int_1	.092	.0315	2.94	0.00	0.14	0.27

To examine H2, the highest-order unconditional interaction of HRA and DL (X×W) in the PROCESS output was evaluated. It was found to have a p-value below .05, indicating a significant interaction effect. The interaction statistics for HRA and DL and their influence on the association between HRA and EIWB are presented in Table VI. The results reveal a significant

moderation effect (p = 0.000). Thus, it can be concluded that H2 is supported, and the data literacy of HR professionals represents a statistically significant moderator of the relationship between HR analytics and employees' innovative work behavior.

Table 6
Test of highest order unconditional interaction

	R2 –change	F	df1	df2	P
X×W	0.0493	18.41	1.00	246.00	0.0000

The focal predictors' conditional effects at different moderator values were examined to better understand the moderating effects, as demonstrated in Table 7. The findings reveal that the relationship between HR analytics and employees' innovative work behavior could be stronger for high data literacy than for low levels. However, as illustrated in Table 7, the strength of the association between HR analytics and employees' innovative work behavior increased as the level of data literacy increased.

Table 7
Conditional effects of the focal predictors at values of moderator (s)

HRA	Effect	Se	T	P	LLCI	ULCI
3.794	1.902	.1024	16.988	0.00	1.676	2.104
4.971	2.690	.0590	42.420	0.00	2.511	2.780
5.270	3.214	.0784	39.957	0.00	3.185	3.496

5. Discussion

The present study investigates the moderating role of HR professionals' data literacy on the relationship between HR analytics and employee innovative work behavior in large companies in Jordan. The results show that HR analytics positively impacts an employee's innovative work behavior. Herewith, it has potential to create a culture of organizational innovation (Ameer et al., 2023). According to the Resource-Based View Theory, organizations leverage HR analytics to identify and measure their employees' unique skills, knowledge, and competencies. By assessing employees' productivity, expertise, skills, and training data, valuable insights are gained concerning the key human capital factors, defining the conditions under which they can foster new and innovative ideas (Marr, 2018). This information is crucial for creating an environment that supports the development and application of novel concepts and for tailoring HR strategies that can promote and incentivize the behaviors (Zafar et al., 2022). From the performance evaluation perspective, human resources analytics play a key role in enhancing the employees' knowledge and skills by relying on innovative-based training programs designed to address recurring issues faced by an organization (Saks, 2021). Moreover, the practice helps explore an organization's level of employee engagement, collaboration, and reciprocity patterns to understand the quality of organizational relationships. Organization's HR professionals can determine which practices and interactions foster innovation by assessing employee engagement, collaborative behaviors, and recognition program outcomes (Margherita, 2022; Schiemann et al., 2018). Supported by Social Exchange Theory, the information gathered via this approach helps create targeted interventions that emphasize the role of innovative reciprocation, recognition, and reward. As a result, workers become more motivated to offer new ideas and solutions, which sustains innovative behaviors over long periods (Subhashini et al., 2019). When analyzed through the prism of Information Processing Theory, human resources analytics grants unique insights into how people access, process, and integrate past information to generate new, innovative ideas. The described insights help explore the cognitive factors that make up innovative workers, such as creativity, problem-solving, critical thinking, and decision-making skills (Kmetz, 2020; Rogers et al., 1999).

Scholars emphasize the importance of HR data analysis, notably predictive analysis, in allowing supervisors to foresee obstacles and opportunities in the future by identifying patterns and trends. The outcome of such an analysis enables the company to foster its proactive skills to resolve problems and implement new ideas before they amplify (Fitz-Enz & John Mattox, 2014; Jaffar et al., 2019). In this regard, HR data analysis is associated with firm innovation as it coincides with the firm's adaptive management style (Kim et al., 2021).

Another essential element the study revealed as having a positive effect on the relationship between HR analytics and the employee's innovative behavior at work was the literacy of the data. HR professionals with a good grasp of interpreting data have gained much experience analyzing employees' information using human resource analytics (Bahuguna et al., 2023; Bandari, 2020; Jiang & Akdere, 2022). They can examine and act on the correlation between employees' behaviors and outcomes and their effects on innovative work behavior (Fitz-Enz & John Mattox, 2014; Jaffar et al., 2019). For this to happen, they must be able to identify the emergence of trends, patterns, and connections that relate to the employee's innovative behavior at work. By analyzing employees' information and implementing human resource analytics, HR professionals with data skills can develop initiatives and strategies that meet an organization's goals and the skills and abilities of employees. They can also find the factors affecting their innovative behavior at work, like the influence of training, control, and the work environment, and make precise modifications to create an organizational climate for innovation (Saks, 2021; Zafar et al., 2022). They can also spot gaps in the talent and skills they need by exploiting the information provided by human resource

analytics and developing programs that improve the abilities and frame of mind required for innovative behavior at work (Marr, 2018; Saks, 2021). Providing employees with knowledge and the basis for promoting an innovation culture is critical. One method is to implement a recognition system for employees and utilize human resource analytics to provide data-based ideas to personnel, encouraging continuous improvement and reinforcing an organizational ethos of innovation (Ameer et al., 2023; Franke & Hiebl, 2023). In addition, HR professionals must use evolved, quick human resource analytics to alter the direction taken by HR to ensure that they can seize such opportunities as organizational goals shift, improving innovative behavior at work (Fitz-Enz & John Mattox, 2014; Jaffar et al., 2019; Kim et al., 2021; Subhashini et al., 2019). Additionally, they can help the organization grasp opportunities for change by detecting new trends and encouraging employee innovative behavior and engagement early to help organizations benefit from this change (Fitz-Enz & John Mattox, 2014; Jaffar et al., 2019; Pothier & Condon, 2020).

6. Practical and theoretical implications of the study

This study offers multiple practical and theoretical implications for businesses in the modern world. Strategically, understanding the strong relationship between HR analytics and innovative work behavior sheds light on how strategic investment in HR analytics tools and processes can benefit organizations. The study's results showed the significance of data literacy as a critical moderating factor in increasing the relationship between HR analytics and innovative works-related behavior. Therefore, companies should encourage their employees to understand data to increase their comprehension and effectively use HR analytics to improve decision-making in the framework of innovative contributions. As a result, organizations can develop the critical data literacy skills required to enhance talent management, data-informed talent spotting, and data-informed employee-development strategies; successful companies are better positioned to support their long-term growth and success. Furthermore, to provide targeted interventions, analytical data can be used to help stimulate creative thinking and idea creation. A company might benefit from understanding staff behaviors from the perspective of recent research in multiple capacities. The study also validated several extant theories, including the Resource-Based Perspective, Social Exchange Theory, and Information Processing Theory. These theories can give an excellent example of how data literacy, HR analytics, and innovation apply to the context of organizations and can be the basis of further studies.

7. Conclusion

This study has explored the relationship linking human resources analytics and employees' innovative behavior and analyzed the moderating role of human resources professionals' data literacy. The results suggest that HR analytics positively relates to staff's innovative behavior and that data literacy increases this correlation positively. Therefore, the advantages of empowering human resources professionals with the lucid abilities required to understand HR analytics to elicit them in decision-making and utilization in artistic work within an organization speak for themselves. In contrast, HR analytics should be utilized to stimulate innovative behavior in a business, while data literacy will be a vital facilitator of this effect. This implication is based on existing theories of social exchange, Resource-Based View, and information processing. The current research makes a significant contribution by closing the gap between theory and practice and providing new insight into the interconnections of HR analytics, data literacy, and innovative behavior.

8. Limitations of the study and future research direction

There is no doubt that this research has provided crucial insights into human resources data analytics. However, the study has limitations, which one should consider to grasp the findings fully.

The study sample was limited to HR professionals from substantial firms in Jordan, which imposes restrictions on how the findings can be generalized to other settings, including medium/small-sized businesses and other geographical regions. As a result, further research needs to address this issue. Also, the study utilized a cross-sectional correlational-predictive design to uncover associations between variables. Thus, further experimental research might be needed to establish causality. Additionally, since the data collection relied on self-reported information through an online survey, there is a concern about potential bias. Though participants' honesty is assumed, it cannot be verified. Hence, unbiased data collection methods are imperative for future research accuracy. Lastly, the study focused on HR analytics, data literacy, and innovative behavior. Expanding exploration to variables like organizational culture, strategy, structure, and other aspects such as employee retention, talent development, and training program effectiveness would enrich the existing literature.

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