

Evaluating the Effects of Environmental Factors on the Adoption of HR Analytics in Nepalese Organizations

Shanti Devi Chhetri*, Chander Mohan Gupta**

*School of Business, Pokhara University, Pokhara, Nepal

**Faculty of Management Sciences, Shoolini University, India

Received: 22 September 2024

Reviewed: 25 November 2024

Accepted: 10 December 2024

Published: 31 December 2024

Correspondence:

Shanti Devi Chhetri
shantichhetri@pusob.edu.np

Citation: Chhetri, S. D., & Gupta, C. M. (2024). Evaluating the effects of environmental factors on the adoption of HR analytics in Nepalese organizations. *The Journal of Business and Management*, 8(2), 150-164
<https://doi.org/10.3126/jbm.v8i2.76154>

Abstract

Background: Human resource (HR) analytics has drawn important interest from organizations since it assists companies in managing and sharing data more flexibly and economically and enables scalable business operations by providing flexible storage solutions. However, organizations in Nepal face many issues that influence the acceptance of HR analytics.

Objectives: The goal of this study is to find out the impact of environmental factors on HR analytics adoption in Nepalese organizations.

Methods: Based on a quantitative approach and using a self-administered questionnaire with 205 responses from various types of organizations were selected through purposive sampling techniques for data collection. Descriptive and inferential statistical techniques were applied to analyze the data using SPSS AMOS.

Results: The results indicate that employee orientation and trading partner pressure are the elements that affect HR analytics adoption in Nepalese organizations. While external pressure does not have any effect on the usage of HR analytics.

Conclusion: The findings show that it is important to train and make employees aware of HR analytics for easy adaptability. The organization should emphasize educating employees on data analytics. Also, the trading partner pressure plays a critical role, it is important to collaborate with trading partners to encourage the adoption of HR analytics. Since external pressure does not impact, it is not necessary to rely on competitors for the adoption of analytics. The results of this study are especially noteworthy since they highlight the enormous difficulties the organization experiences in trying to modify management practices while also adding to our understanding of management theory and the adoption of technology.

Keywords: Adoption, developing nations, human resource, human resource analytics, trading partner pressure

JEL Classification: O15, C30

Introduction

The growing challenges of market competition made many prosperous companies to adopt data analytics as a means of identifying new avenues for promoting their products and services (Davenport, 2019). In fact, 77% of large organizations view data analytics as an essential component of their business operations (Weam et al., 2023). It is stated that in order to achieve the intended influence on company performance, data analytics should be used across the whole organization. The Human Resources (HR) department should surely be a part of this as it manages the company's most valued asset, its people. Managing people increasingly means being abreast of ongoing developments and changes in order to spot new market opportunities for companies (Mishra & Lama, 2016; Pongpisutsopa et al., 2020). In order to become an innovative organization, it is necessary to reimagine classic HR roles, support new processes, and attract and retain creative personnel (Penpokai et al., 2023). HR analytics has a big impact on how businesses work with their employees (Fritz-Enz, 2010; Momin & Mishra, 2014; van der Togt & Rasmussen, 2017). HR analytics have grown dramatically as a result of the digitization of HR, which was fueled by the increased use of information technology (McCartney et al., 2020). Opportunities for HR practitioners to employ technology-generated data to assist human resource management (HRM) and business solutions, particularly decision-making, are emerging concurrently with the digitization of HRM (van den Heuvel & Bondarouk, 2017). HR analytics may be applied as a data-driven strategy for analytics-based personnel management. (Muhammad et al., 2023), who looked at adoption barriers, found that almost 71% of the businesses saw HR analytics adoption as a significant challenge. While the majority of businesses still struggle with HR analytics adoption, about 23% of organizations worldwide have successfully integrated HR analytics at the organizational level. Adoption of new technologies, such as HR analytics, is critical to an organization's capacity to retain its competitive edge in the industry, and it has become a basic strategy to ensure successful information technology (IT) resource management (Harfoushi et al., 2016).

In spite of the fact that HR analytics has been hailed as a new technological advancement that can offer adopters a number of benefits at the tactical, strategic, and operational levels, the rate at which HR analytics adoption is occurring is not as rapid as anticipated (Verma & Chaurasia, 2019). While HR analytics adoption has been widely studied in developed economies, there is a scarcity of research addressing the unique challenges and environmental factors influencing its adoption in developing countries, particularly Nepal. There is a lack of empirical studies that combine quantitative and qualitative approaches to evaluate the effects of environmental factors on HR analytics adoption in Nepalese organizations. Previous studies in Asian and European nations have identified a number of variables that affect the implementation of HR analytics by taking into account organization and technology attributes; however, the impact of environmental factors on the implementation of HR analytics has not been extensively studied. The use of technological tools, data, and analytical methodologies to HR makes HR analytics a sophisticated and creative process. The study focuses to explore the determinants influencing the implementation of HR analytics in the organizations of Nepal and have their roots in academic research.

Review of Literature

The term HR analytics has become prominent in HRM and executive leadership spheres (Bennett & Collins, 2015). By improving the accessibility, interpretability, and actionability of data regarding employee traits, behaviour, and performance, HR analytics aims to assist businesses in better understanding their workforce whether viewed as a collective entity, within specific departments or work groups, or at the individual level (Lakshmi & Pratap, 2016). Underpinned by personnel profiles and performance data, this involves the use of predictive analytics, visualization tools, and information systems (Tursunbayeva et al., 2019). Handa and Garima (2014) stated HR analytics is an integrated process that helps to raise

the standard of people-related choices, which in turn raises individual and organizational performance. The majority of HR analytics rely on statistical techniques and analyses, which call for high-quality data, well-selected goals, skilled analysts, leadership, and widespread acceptance that analytics is a valid and beneficial means of enhancing performance. According to Kapoor (2021), HR analytics is the management of important HR related data and documents with the goal of utilizing business analytics models to analyze the collected data and provide the findings to decision-makers so they can make the most appropriate choices. As noted by Lakshmikeerthi and Reddy (2019) HR analytics is a decision-making approach that integrates the best available scientific and corporate knowledge with critical thinking. In order to comprehend the relationship between people management practices and company outcomes like profitability, customer happiness, and quality, it employs data, analytics, and research. Jabir et al. (2019) explain that HR analytics is the process of examining and comprehending how and why events occur, generating alerts on the optimal course of action, and drawing conclusions about the best and worst scenarios that may arise from the data that have been examined. Lawler and Boudreau (2021) said that HR analytics encompasses more than just research design and statistics. It also involves relevant data collection and utilization from both inside and outside the HR function, the establishment of appropriate rigour and relevance standards, the formulation of meaningful questions, and the improvement of HR's analytical competencies across the entire organization. van den Heuvel and Bondarouk (2017) considered HR analytics as the methodical process of determining and measuring the human-related variables that influence company results. An analysis of an organization's personnel issues, such as yearly staff turnover and regretful losses, is known as human resource analytics. HR departments have long been gathering enormous volumes of HR data in order to analyze it. Unfortunately, a significant portion of this data goes unused, organizations are using HR analytics as soon as they begin to use this data to analyze their personnel issues. It increases return on investment (ROI) by empowering HR professionals to make data-driven decisions about selecting, managing, and retaining staff (Malla, 2018). Through the use of digitally powered analytics solutions, HR analytics has grown up from a modest organizational project to a sophisticated diagnostic and predictive tool that can improve employee engagement and retention and benefit entire organizations (Edwards, 2018). Along with the development of business analytics as a fundamental organizational competency, human resource management has progressively adopted more sophisticated models and techniques for data analysis and visualization to support strategic decision-making and meet the demands of the organization's executives and key decision-makers. In order to analyze people-related risks, performance traits, involvement and culture, and career paths HR analytics combines several methods and tools with a strong multidisciplinary element (Bersin, 2013; Margherita, 2021).

An extensive body of academic research demonstrates how the value of HR analytics in organizations is increasing. Similar to how the finance department monitors ROI (Boakye & Ayerki Lamptey, 2020) discuss the possible Impact of Workforce Strategy on Organizational Performance and offer workable techniques for assessing and managing HR assets. Roberts et al. (2021) said that for new technology to thrive, it must not only be technically proficient but demonstrate to prospective buyers in a manner that organizations, leaders, and end-users are interested in. Recognizing the psychological factors influencing technology implementation is a crucial element in achieving this success. Most of all, the study concluded that leaders may influence organizational beliefs, resources, and the way that technology adoption is incorporated. Researcher such as Malik et al. (2021) sought to identify the variables driving Block Chain Technology (BCT) adoption across Australian organizations. The study's findings revealed that technological factors such as disintermediation, perceived benefits, information transparency, and compatibility; organizational factors such as organizational innovativeness, organization support, and learning capability of the organization, and environmental factors such as trading partner readiness, support from the government, competition intensity, and standards uncertainty all have a significant role in the organizational adoption of BCT in Australia. However, Communication, innovativeness,

expertise, product quality, and motivation were identified to be the five most critical variables for effectively transferring technology (Singhai et al., 2021).

Alaskar et al. (2021) used the TOE framework and the institutional theory to investigate the influence of external variables and the intervening function of top management's support (TMS) in Saudi firms to use big data analytics (BDA) in supply chain management (SCM). The statistical analysis using SmartPLS shows that vendor support and competitive pressure had a direct influence on the desire for SCM to employ BDA. Regarding the ways in which these two factors affected intention, TMS did not appear to be a major mediating element. Low et al. (2011) examined *The Variables Influencing Cloud Computing Adoption by High-Tech Industry Companies*. They took eight factors such as business size, technological readiness, compatibility, complexity, competitive pressure, trade partner pressure, and TMS. The results showed that the adoption of cloud computing is significantly affected by relative advantage, TMS, business size, competitive pressure, and trade partner pressure features. (Tajudeen et al., 2018) studied *The Causes and Effects of Social Media Use in Businesses*. The TOE framework is employed in the research, along with a few antecedent characteristics unique to social media implementation in businesses. The findings showed a favourable correlation between organizational use of social media and relative advantage. Customers' and competitors' pressure, among other external factors, has a beneficial impact on social media usage.

Sharma et al. (2023) applied the TOE paradigm to examine and rank 17 big data adoption (BDA) factors and demonstrate a causal relationship between the determinants and organizations' performance in the tourism and hospitality industry. The findings showed that more than organizational and environmental variables, technical elements, specifically, big data quality and predictive analytics accuracy have an influence on big data adoption and business performance. Also, Hsu et al. (2014) established a cloud service adoption model that addresses the intention to adopt, pricing strategies, and deployment methods using the TOE paradigm of innovation diffusion theory. Using 200 Taiwanese companies, the research model was empirically evaluated. According to the results, cloud adoption is still in its early stages due to the extremely low adoption rates. Perceived advantages, business concerns, and IT capacity within the TOE context are key factors that influence cloud computing adoption, but competitive pressure does not. Bolonne and Wijewardene (2020) investigated how several factors might affect the extent to which BDA may be implemented in the Sri Lankan setting. When the organizational context components such as vision and strategy, leadership and governance, organizational structure, talent strategy, and development were examined independently, they all shown a substantial beneficial effect on the attitude towards implementing BDA. According to the study, organizations in the apparel sector that want to promote data-driven decision-making through increased use of BDA are specifically supported to focus on data-related infrastructure capabilities, strategy and goal setting, dynamic changes in consumer demands, transparency, and understandability, as well as enhancement of the effectiveness of users' job roles.

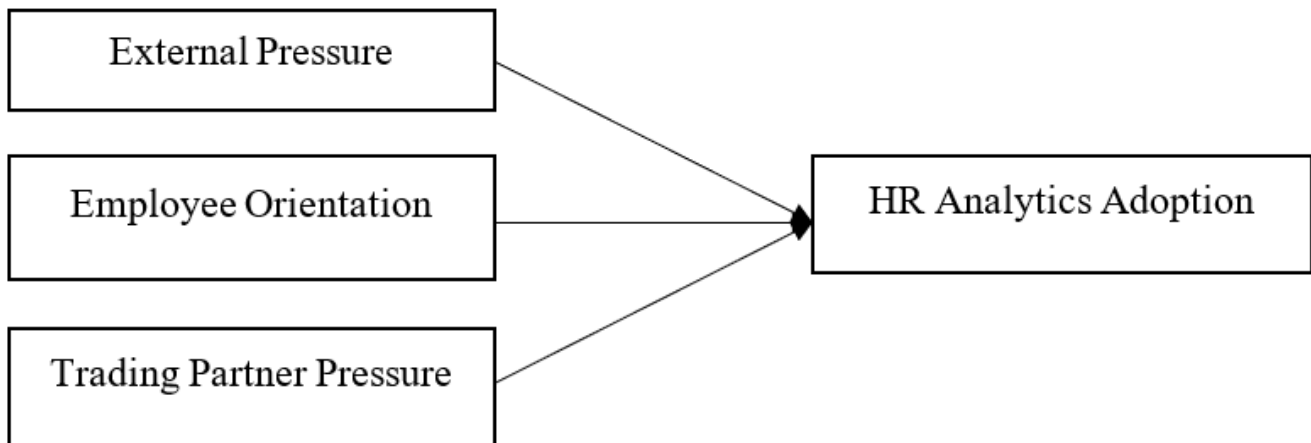
Furthermore, Qalati et al. (2020) show how social media adoption in Pakistani SMEs is influenced by technical, organizational, and environmental (TOE) aspects. The study's findings show that the TOE factors namely, TMS, visibility, interactivity, relative advantage, and institutional pressure have a direct effect on SMEs' usage of social media, which enhances SMEs' performance. To assess the variables driving cloud computing adoption in Portuguese firms, Oliveira et al. (2014) developed a study model based on the innovative features from the diffusion of innovation (DOI) theory and the TOE framework. Additionally, the report examines the variables impacting cloud computing implementation in the services and industrial sectors. The findings show that five elements affect cloud computing adoption. These include the size and complexity of the business, the support of upper management, technical readiness, and relative advantage. In order to establish a conceptual model for the usage of cloud computing, Alghushami et al. (2020) studied the effects of TOE factors in Yemeni higher education

institutions (HEIs). The data indicates that the usage of cloud computing is positively impacted by relative advantages, competitive pressure, dependability, compatibility, safety, technological readiness, organization support, governing policy, and, with the exception of tribe culture, which has a negative significant influence.

The authors evaluated scientific papers aimed at studying HR analytics adoption at the organizational level in order to emphasize the direct influence of environmental variables on adoption.

Figure 1

Proposed Research Model



In this research, external pressure refers to the influence exerted by rival organizations that have successfully implemented HR analytics to enhance their workforce management and decision-making processes. By Porter and Millar (1985) perspectives, integration of innovative IT technology by competitors may change the industry structure, change the laws of competition, and generate whole new value offers and enterprises. Firms would thus be compelled to implement comparable innovations in order to maintain their competitiveness. Several studies support the concept that the more external pressure, the higher the motivation for a company to use IT (Alaskar et al., 2021; Low et al., 2011; Nurdin et al., 2012; Penttinen & Tuunainen, 2010). Several empirical studies suggested employee orientation is an important determinant of HR analytics adoption (Ekka & Singh, 2022).

In the current study, trading partner pressure refers to the influence exerted by an organization’s business partners, such as suppliers, distributors, or clients, to implement HR analytics. Many businesses rely on trading partners for IT design and job implementation. Most of the existing studies demonstrate how trading partner pressure is a crucial factor in IT adoption and use. Previous trading partner history and past initiatives can have an impact on whether or not to accept a new Information Technology advancement. Past studies show the impact of trading partner pressure on the adoption of technology (Gutierrez et al., 2015; Harfoushi et al., 2016; Sharma et al., 2023).

Materials and Methods

The current study employs a quantitative research approach, the HR managers were the critical respondents selected since they were thought to be the most knowledgeable about the HR analytics used in the organization. Different sectors are selected for this study because, to the best of the researcher’s knowledge, this is the first study conducted in Nepal focusing on HR analytics. By including multiple sectors, the study aims to explore the diverse applications and adoption levels of HR analytics across industries. This approach provides a comprehensive understanding of how HR analytics is utilized in

the Nepalese context. A self-structured questionnaire was used for the collection of data. A total of 205 valid responses were employed in the analysis of data. The responses were recorded on a five-point Likert scale (1 being “strongly disagree,” and 5 being “strongly agree”). The reliability of the items is evaluated using Cronbach’s Alpha and composite reliability, while the validity of the items is assessed using the Fornell and Larcker criterion. The suggested model was examined using AMOS structural equation modelling, a method that is widely applied in management and related sectors. It is among the most thorough and reliable techniques for variance analysis.

Results and Discussion

Organizations and Respondents’ Information

Table 1

Organizations and Respondents’ Information

| Variables | Categories | Frequency | Percent |
|--|------------------------------------|------------------|----------------|
| Gender | Male | 117 | 57.1 |
| | Female | 88 | 42.9 |
| Type of Organizations | IT | 28 | 13.7 |
| | Manufacturing | 21 | 10.2 |
| | Banking and Financial Institutions | 69 | 33.7 |
| | Hospitals | 20 | 9.8 |
| | Hotels | 11 | 5.4 |
| | Automobiles | 7 | 3.4 |
| | Insurance | 11 | 5.4 |
| | Others | 38 | 18.5 |
| | Qualification | Bachelor | 74 |
| Masters and above | | 131 | 63.9 |
| Total experience as HR | 1-2 years | 56 | 27.3 |
| | 3-5 years | 78 | 38.0 |
| | 5 years and above | 71 | 34.6 |
| No. of years of organization establishment | 0-5 years | 15 | 7.3 |
| | 6-10 years | 45 | 22.0 |
| | 11 years and above | 145 | 70.7 |
| Organization size | 1-50 | 47 | 22.9 |
| | 51-100 | 35 | 17.1 |
| | 101 and above | 123 | 60.0 |
| Ratio of technology savvy HR | very few | 45 | 22.0 |
| | 50 percent of the employees | 105 | 51.2 |
| | All | 55 | 26.8 |
| Collection of employee data | yes | 202 | 98.5 |
| | No | 3 | 1.5 |
| | Total | 205 | 100 |

Table 1 indicates that among 205 respondents, 57.1 percent represent male and 88 percent female. The majority of those surveyed, 33.7 percent were from banking and financial institutions, followed by other forms of organizations. In terms of qualification, most of the respondents 63.9 percent hold a master degree. Regarding total experience as HR majority of the respondents (38 percent) have 3-5 years of experience. In terms of duration of organization establishment, most of the organization (70.7 percent) is established for 11 years and above. Regarding organization size, majority of the organizations (60 percent) had 110 or more employees. In the context of ratio of technology savvy HR in organization, most of the organization (51.2 percent) had 50 percent of the employees as technology savvy. Lastly, regarding the collection of employee data, majority of the organization (98.5 percent) collects employee related data.

Feasibility of Factor Analysis

The feasibility of applying factor analysis on the dataset is measured through two measures the Kaiser-Meyer-Olkin (KMO) statistic and Bartlett’s Test of Sphericity shown in Table 2. It is concluded that the data is viable because the obtained KMO value of 0.918 is more than 0.5. According to the results of the Bartlett’s test of sphericity, the correlation matrix is not an identity matrix since the Chi-Square value is 3441.79 with a significant value of 0.000.

Table 2

KMO and Bartlett’s Test

| | | |
|---|--------------------|---------|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | 0.918 |
| Bartlett’s Test of Sphericity | Approx. Chi-Square | 3441.79 |
| | df | 300 |
| | Sig. | 0.000 |

Examination of Measurement Model

The measurement model results (reliability, validity, and model fit indicators) are presented in the table 3, 4, and 5. The scales’ reliability was assessed using Cronbach’s alpha (CA), with a recommended threshold of >0.7 as proposed by Hair et al. (2018). Subsequently, the study assessed convergent validity based on the guidelines from (Li et al., 2020). For internal consistency reliability, it was essential for the composite reliability (CR) to be equal to or greater than 0.7 (Hair et al., 2011). Larcker (2012) recommended that the average variance extracted (AVE) should be ≥0.5 to establish convergent validity, as shown in Table 3, which presents CA, CR, and AVE, to evaluate reliabilities, internal consistency, and convergent validity. Regarding discriminant validity (refer to Table 4), the square of AVE for each variable must exceed the correlation value among the variables. The study took six items for external pressure, five items for employee orientation, and six items for trading partner pressure. A few items were omitted during the analysis of model fit because those items were causing poor model fit indices. According to Hair et al. (2018) the threshold value of CMIN/DF is 5. Additionally, GFI, NFI, and CFI should surpass the 0.90 threshold. Furthermore, the RMSEA cut-off value is 0.08. Figure 2 and Table 5 show that the parameters such as CMIN/DF, GFI, NFI, CFI and RMSEA have acceptable value range for the model to be fit.

Table 3

Result of CFA, Reliability and Validity Test

| Constructs | Items | Factor Loadings | Critical Ratio | P-value | Cronbach's | Composite Reliability | AVE |
|--------------------------|-------|-----------------|----------------|---------|----------------|-----------------------|-------|
| External Pressure | EP2 | 0.721 | 10.355 | *** | Alpha 0.850 | 0.851 | 0.589 |
| | EP4 | 0.787 | 11.401 | *** | | | |
| | EP5 | 0.774 | 11.207 | *** | | | |
| | EP6 | 0.785 | ---- | ---- | | | |
| Employee Orientation | EO2 | 0.790 | 10.641 | *** | 0.814 | 0.815 | 0.594 |
| | EO3 | 0.743 | 10.106 | *** | | | |
| | EO4 | 0.779 | ---- | ---- | | | |
| Trading Partner Pressure | TP1 | 0.850 | ---- | ---- | 0.918 | 0.920 | 0.699 |
| | TP2 | 0.863 | 15.820 | *** | | | |
| | TP3 | 0.875 | 16.183 | *** | | | |
| | TP4 | 0.874 | 16.154 | *** | | | |
| | TP5 | 0.705 | 11.563 | *** | | | |
| HR Adoption | HRA1 | 0.851 | ---- | ---- | 0.864 | 0.869 | 0.625 |
| | HRA2 | 0.811 | 13.113 | *** | | | |
| | HRA3 | 0.712 | 11.066 | *** | | | |
| | HRA5 | 0.782 | 11.066 | *** | | | |

Table 4

Discriminant validity: Fornell and Larker

| | EP | EO | TPP | HRA |
|-------------------|-------|-------|-------|-------|
| Model fit indices | 0.767 | | | |
| EO | 0.704 | 0.771 | | |
| TPP | 0.629 | 0.571 | 0.836 | |
| HRA | 0.532 | 0.555 | 0.52 | 0.791 |

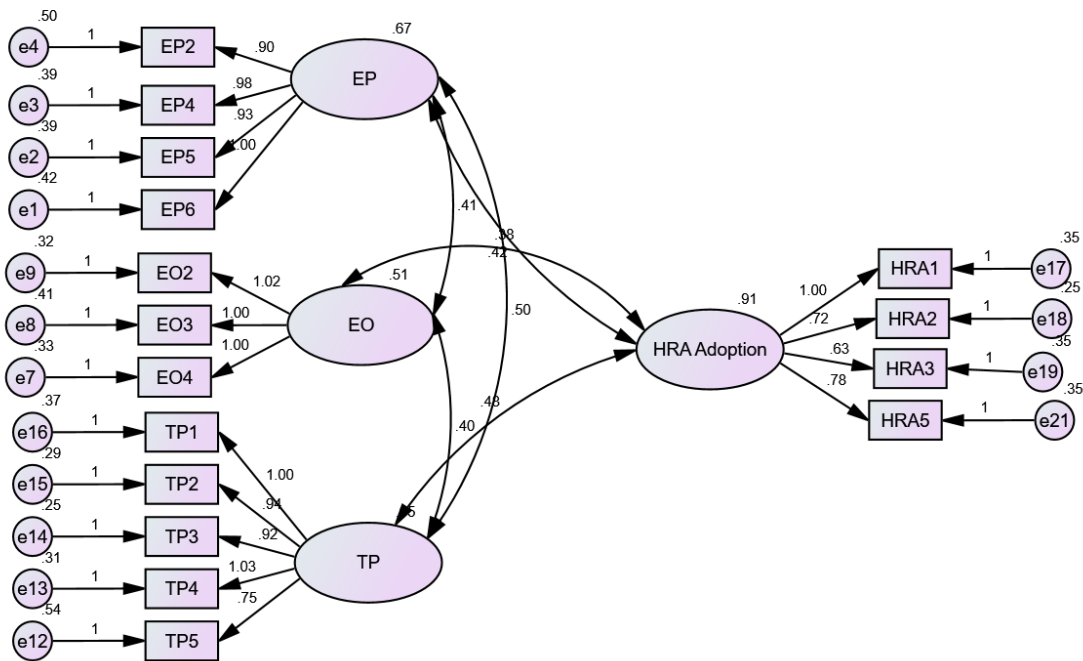
Table 5

Model fit indices

| Fit Indices | Criteria | Calculate value | Remarks |
|-------------|--------------|-----------------|----------|
| CMIN/DF | < 3 | 1.849 | Good fit |
| GFI | 0.9 or above | .903 | Good fit |
| NFI | 0.9 or above | .914 | Good fit |
| CFI | 0.9 or above | .958 | Good fit |
| RMSEA | < 0.08 | .065 | Good fit |

NOTE: CMIN/ DF = chi-square/degree of freedom; GFI = goodness-of-fit index; NFI = normed fit index; CFI = comparative fit index; RMSEA = root mean square error of approximation.

Figure 2
Measurement Model



Examination of Structural Model

Table 6 presents a thorough overview of the evaluations conducted using the structural model, while Figure 3 indicates the path coefficients along with their relevant significance levels.

Figure 3
Path Diagram

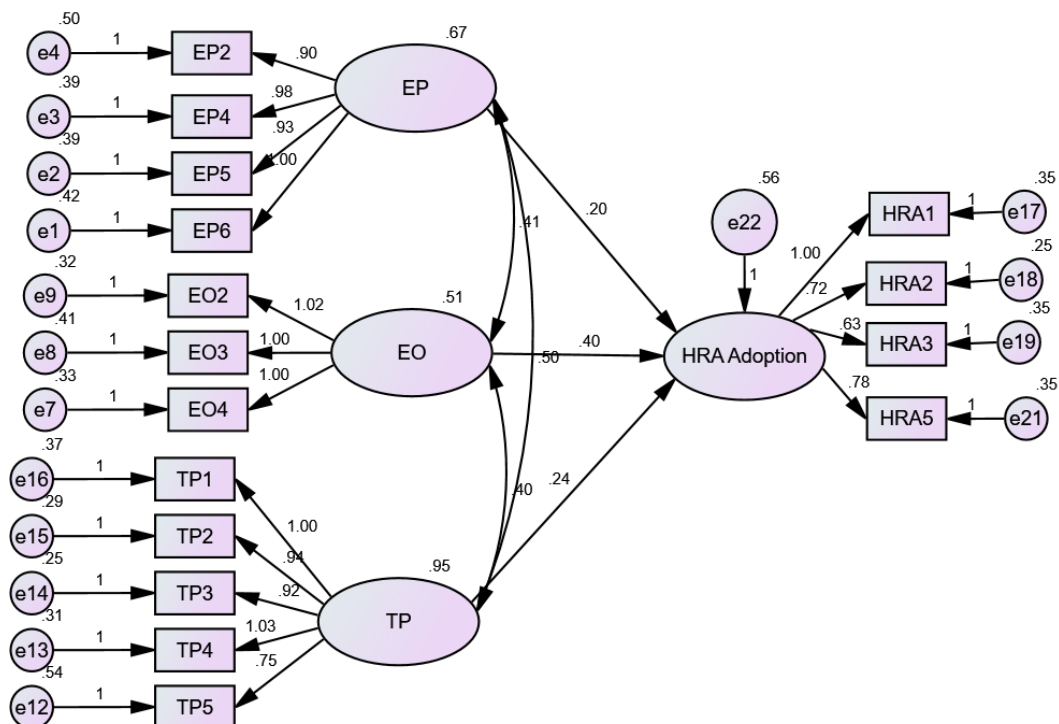


Table 6

Path Analysis

| | Estimate | S.E. | C.R. | P |
|--------------|----------|-------|-------|-------|
| HRA <--- EP | 0.197 | 0.139 | 1.42 | 0.156 |
| HRA <--- EO | 0.395 | 0.155 | 2.552 | 0.011 |
| HRA <--- TPP | 0.238 | 0.09 | 2.657 | 0.008 |

Table 6 inferred that external pressure is not statistically significant to HR analytics adoption in Nepalese organization. However, employee orientation and trading partner pressure is statistically significant with HR analytics adoption with p value = 0.011 and 0.008 respectively. Thus, the study incorporates that employee orientation and trading partner pressure is significant to HR analytics adoption in the organizations of Nepal.

The research aims to discover the factors influencing the adoption of HR analytics in Nepalese organizations. After conducting a thorough review of the existing body of literature, three potential determinants namely external pressure, employee orientation, and trade partner pressure, based on environmental variables were investigated. In particular, this research focused on how independent variables in the environmental setting affected the dependent variable (adoption of HR analytics). Out of three variables, the external pressure was not statistically significant to the implementation of HR analytics which is aligned with the prior analysis (Al-Jabri & Alabdulhadi, 2016; Hsu et al., 2014; Oliveira et al., 2014) and contrary to others (Qalati et al., 2020; Simoes et al., 2019; Tajudeen et al., 2018). The employee orientation was found to be statistically significant to HR analytics adoption which supports the previous research (Ekka & Singh, 2022). The trading partner pressure was statistically significant to HR analytics adoption which supports the past studies (Gutierrez et al., 2015; Low et al., 2011; Sharma et al., 2023) and contrary to others (Al-Jabri & Alabdulhadi, 2016). This pressure results from trade with corporate partners as well as from rivalry within the sector, particularly those who are employing HR analytics. Organizations may decide to embrace HR analytics if they believe it is vital to conduct business with their trade partners. Another form of pressure comes from industry, where organizations may sense they must use HR analytics to maintain competitiveness, especially in light of the widespread use of HR analytics by their rival companies. In Nepal, the implementation of HR analytics is still in its early stages, and businesses are still debating whether to use it (Chhetri et al., 2023). Business organizations do not yet believe that HR analytics might give them a competitive advantage.

The findings of this study provide insightful information that managers may use to make well-informed choices about using HR analytics. Employee orientation, a crucial aspect frequently ignored in earlier studies, was included in this study as a critical environmental context element. By emphasizing the need to consider employee viewpoints while bringing new technology into their organizations, this research emphasizes the relevance of helping managers understand employees better. The research contributes significantly to the corpus of knowledge and addresses a gap in HR analytics and the adoption of new technology. The discovery of advantages offers a critical foundation for further research into the obstacles to HR analytics implementation in businesses. Previous papers mostly focused on developed nations, thus this paper provides the environmental factors affecting the adoption of HR analytics in developing nations like Nepal. The results of this study are especially noteworthy since they highlight the enormous difficulties the organization experiences in trying to modify management practices while also adding to our understanding of management theory and the adoption of technology.

Conclusion and Suggestions

This research paper assesses the environmental elements that impact the application of HR analytics within organizations in Nepal, as perceived by HR managers. This study represents an initial endeavor to gain insights into the determinants shaping the acceptance of HR analytics in the Nepalese context. The results indicate that employee orientation and trading partner pressure are the elements that affect HR analytics adoption in Nepalese organizations. While external pressure does not have any effect on usage of HR analytics.

There were a few limitations found, nevertheless, which have provided new opportunities for further study. For instance, even though the questionnaire collected and assessed over 205 useable replies, not enough responses from each industrial sector or organization size were provided. Additional research might be conducted based on certain business sizes or the type of activities they are engaged in by focusing on one business sector. Different nations have diverse traits including culture, rivalry, commercial partners, and governmental rules and regulations. It is possible to compare the findings of related studies by conducting studies in different nations. Further research can be carried out by taking mediating factors like organizational culture and top management support. This study is the first step towards identifying the role of different factors affecting adopting HR analytics which offers valuable insights for HR professionals, as well as the policy makers, decision makers, and technology marketers targeting the HR sector and developers focused on HR technology. technology marketers targeting the HR sector and developers focused on HR technology.

Author contribution statement

S.D.C.: Conceptualization, methodology, data curation, writing, review and editing. C.M.G.: Conceptualization data curation, formal analysis, and supervision. All authors addressed the comments of reviewers and finalized the manuscript.

Funding

There is no funding support for this study.

Declaration statement

The authors declare no conflict of interest.

References

- Al-Jabri, I. M., & Alabdulhadi, M. H. (2016). Factors affecting cloud computing adoption: Perspectives of IT professionals. *International Journal of Business Information Systems*, 23(4), 389–405. <https://doi.org/10.1504/IJBIS.2016.080215>
- Alaskar, T. H., Mezghani, K., & Alsadi, A. K. (2021). Examining the adoption of Big data analytics in supply chain management under competitive pressure: evidence from Saudi Arabia. *Journal of Decision Systems*, 30(2–3), 300–320. <https://doi.org/10.1080/12460125.2020.1859714>
- Bennett, C., & Collins, L. (2015). HR and people analytics: Stuck in neutral. In *Global Human Capital Trends 2015* (pp. 71–77). Deloitte University Press.
- Bersin, J. (2013). High-impact talent analytics : Building a world-class HR measurement and analytics function. In *Bersin by Deloitte* (pp. 1–2). ... by Deloitte/Josh Bersin, Karen O' <http://marketing.bersin.com/rs/bersin/images/hital100113sg.pdf>
- Boakye, A., & Ayerki Lamptey, Y. (2020). The rise of hr analytics: Exploring its implications from a developing country perspective. In *Journal of Human Resource Management* (Vol. 8, Issue 3, p. 181). [article.hrmanag.org. https://doi.org/10.11648/j.jhrm.20200803.19](https://doi.org/10.11648/j.jhrm.20200803.19)
- Chhetri, S. D., Kumar, D., Ranabhat, D., & Sapkota, P. (2023, April). Validating the Measurement Scale Items on Readiness to Adopt Human Resource Analytics in the Organizations of Nepal. In *International Conference on Intelligent Computing & Optimization* (pp. 3-13). Cham: Springer Nature Switzerland.
- Davenport, T. H. (2019). Is HR the most analytics-driven function? In *Harvard Business Review* (pp. 2–5).
- Edwards, M. R. (2018). HR metrics and analytics. *E-HRM*, 89–105. Routledge <https://doi.org/10.4324/9781315172729-6>
- Ekka, S., & Singh, P. (2022). Predicting HR professionals' adoption of HR analytics: An Extension of UTAUT Model. *Organizacija*, 55(1), 77–93. <https://doi.org/10.2478/orga-2022-0006>
- Fritz-Enz, J. (2010). The new HR analytics: predicting the economic value of your company's human capital investments. *Choice Reviews Online* 48(04), 48–2175. AMACOM. <https://doi.org/10.5860/choice.48-2175>
- Gutierrez, A., Boukrami, E., & Lumsden, R. (2015). Technological, organizational and environmental factors influencing managers' decision to adopt cloud computing in the UK. *Journal of Enterprise Information Management*, 28(6), 788–807. <https://doi.org/10.1108/JEIM-01-2015-0001>
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2018). *Multivariate data analysis* (Eight Edition). Cengage Learning EMEA.
- Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing theory and Practice*, 19(2), 139-152. <https://doi.org/10.2753/MTP>
- Handa, D., & Garima. (2014). Human resource (HR) analytics: Emerging trend in HRM. *International Journal of Research in Commerce & Management*, 5(6), 59–62. <http://search.ebscohost.com/login6iz5MgmxHup6XNKiRFlAGmFZXW4nQBUJ2yt%2BGxbAbPIduzg%3D%3D&crl=c>
- Harfoushi, O., Akhorshaideh, A. H., Aqqad, N., Janini, M. Al, & Obiedat, R. (2016). Factors affecting the intention of adopting cloud computing in Jordanian hospitals. *Communications and Network*, 08(02), 88–101. <https://doi.org/10.4236/cn.2016.82010>

- Hsu, P. F., Ray, S., & Li-Hsieh, Y. Y. (2014). Examining cloud computing adoption intention, pricing mechanism, and deployment model. *International Journal of Information Management*, 34(4), 474–488. <https://doi.org/10.1016/j.ijinfomgt.2014.04.006>
- Jabir, B., Falih, N., & Rahmani, K. (2019). HR analytics a roadmap for decision making: Case study. *Indonesian Journal of Electrical Engineering and Computer Science*, 15(2), 979–990. <https://doi.org/10.11591/ijeecs.v15.i2.pp979-990>
- Kapoor, S. (2021). HR Analytics for Competitive Advantage. *Financial Intelligence in Human Resources Management*, 337–354. <https://doi.org/10.1201/9781003083870-18>
- Madhavi Lakshmi, P., & Siva Pratap, P. (2016). HR analytics-a strategic approach to HR effectiveness. *International Journal of Human Resource Management and Research (IJHRMR) ISSN (P)*, 2249-6874. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2838824
- LakshmiKeerthi, P. (2019). *Usage of HR Analytics and challenges encountered by Singapore based companies (Doctoral dissertation, Sri Venkateswara University Tirupati)*.
- Larcker, C. F. and D. F. (2012). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18, 39–50.
- Lawler, E. E., & Boudreau, J. W. (2021). The Results of HR Metrics and Analytics. *Human Resource Excellence*, 82–92. <https://doi.org/10.1515/9781503605589-010>
- Li, C., Ahmed, N., Qalati, S. A., Khan, A., & Naz, S. (2020). Role of business incubators as a tool for entrepreneurship development: The mediating and moderating role of business start-up and government regulations. *Sustainability (Switzerland)*, 12(5), 1–23. <https://doi.org/10.3390/su12051822>
- Low, C., Chen, Y., & Wu, M. (2011). Understanding the determinants of cloud computing adoption. *Industrial Management and Data Systems*, 111(7), 1006–1023. <https://doi.org/10.1108/02635571111161262>
- Malla, J. (2018). HR Analytics Center of Excellence. *International Journal of Business, Management and Allied Sciences*, 5, 282-284. <http://www.ijbmas.in/5.S2.18/282-284.pdf>
- Margherita, A. (2021). Human resources analytics: A systematization of research topics and directions for future research. *Human Resource Management Review*, 32(2), 100795. <https://doi.org/10.1016/j.hrmr.2020.100795>
- McCartney, S., Murphy, C., & Mccarthy, J. (2020). 21st century HR: a competency model for the emerging role of HR Analysts. *Personnel Review*, 50(6), 1495–1513. <https://doi.org/10.1108/PR-12-2019-0670>
- Mishra, S. N., & Lama, D. R. (2016). A decision making model for human resource management in organizations using data mining and predictive analytics. *International Journal of Computer Science and Information Security (IJCSIS)*, 14(5), 217–221.
- Momin, W. Y. M., & Mishra, K. (2014). Impression of financial measures in HR analytics. *Journal of Interdisciplinary and Multidisciplinary Research*, 2(1), 87–91. <https://doi.org/10.13140/rg.2.2.12883.73761>
- Muhammad, G., Siddiqui, M. S., Rasheed, R., Shabbir, H., & Sher, R. F. (2023). Role of external factors in adoption of HR Analytics: Does Statistical background, gender and age matters? *Journal of Business Analytics*, 7(1), 1–14. <https://doi.org/10.1080/2573234X.2023.2231966>

- Nuridin, N., Stockdale, R., & Scheepers, H. (2012). The influence of external institutional pressures on local e-government adoption and implementation: A coercive perspective within an Indonesian local e-government context. *Electronic Government: 11th IFIP WG 8.5 International Conference, EGOV 2012, Kristiansand, Norway, September 3-6, 2012. Proceedings 11*, 13-26. Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-33489-4_2
- Oliveira, T., Thomas, M., & Espadanal, M. (2014). Assessing the determinants of cloud computing adoption: An analysis of the manufacturing and services sectors. *Information and Management*, 51(5), 497–510. <https://doi.org/10.1016/j.im.2014.03.006>
- Penpokai, S., Vuthisophon, S., & Saengnoee, A. (2023). The relationships between technology adoption, HR competencies, and HR analytics of large-size enterprises. *International Journal of Professional Business Review*, 8(3), 1–13. <https://doi.org/10.26668/businessreview/2023.v8i3.971>
- Penttinen, E., & Tuunainen, V. K. (2010). Assessing the effect of external pressure in inter-organizational is adoption - Case electronic invoicing. *Lecture Notes in Business Information Processing*, 52, 269–278. https://doi.org/10.1007/978-3-642-17449-0_27
- Pongpisutsopa, S., Thammaboosadee, S., & Chuckpaiwong, R. (2020). Factors affecting HR analytics adoption: A systematic review using literature weighted scoring approach. *Asia Pacific Journal of Information Systems*, 30(4), 847–878. <https://doi.org/10.14329/APJIS.2020.30.4.847>
- Porter, E. M., & Millar, E. V. (1985). How information gives you competitive advantage. In *Harvard Business Review*, 149–152.
- Qalati, S. A., Li, W., Vela, E. G., Bux, A., Barbosa, B., & Herzallah, A. M. (2020). Effects of technological, organizational, and environmental factors on social media adoption. *Journal of Asian Finance, Economics and Business*, 7(10), 989–998. <https://doi.org/10.13106/jafeb.2020.vol7.no10.989>
- Roberts, R., Flin, R., Millar, D., & Corradi, L. (2021). Psychological factors influencing technology adoption: A case study from the oil and gas industry. *Technovation*, 102, 102219. <https://doi.org/10.1016/j.technovation.2020.102219>
- Sharma, M., Gupta, R., Sehrawat, R., Jain, K., & Dhir, A. (2023). The assessment of factors influencing Big data adoption and firm performance: Evidences from emerging economy. *Enterprise Information Systems*, 17(12), 2218160. <https://doi.org/10.1080/17517575.2023.2218160>
- Simoes, A., Oliveira, L., Rodrigues, J. C., Simas, O., Dalmarco, G., & Barros, A. C. (2019). Environmental factors influencing the adoption of digitalization technologies in automotive supply chains. *IEEE international conference on engineering, technology and innovation (ICE/ITMC)*, 1-7. IEEE. <https://doi.org/10.1109/ICE.2019.8792639>
- Singhai, S., Singh, R., Sardana, H. K., & Madhukar, A. (2021). Analysis of factors influencing technology transfer: A structural equation modeling based approach. *Sustainability (Switzerland)*, 13(10), 1–15. <https://doi.org/10.3390/su13105600>
- Tajudeen, F. P., Jaafar, N. I., & Ainin, S. (2018). Understanding the impact of social media usage among organizations. *Information and Management*, 55(3), 308–321. <https://doi.org/10.1016/j.im.2017.08.004>
- Tursunbayeva, A., Pagliari, C., & Lauro, S. Di. (2019). Opportunities and benefits of people analytics for HR managers and employees: Signals in the grey literature. *The 13th Mediterranean Conference on Information Systems (MCIS)*, 1–8. <https://aisel.aisnet.org/mcis2019/31>

- van den Heuvel, S., & Bondarouk, T. (2017). The rise (and fall?) of HR analytics: A study into the future application, value, structure, and system support. *Journal of Organizational Effectiveness: People and Performance*, 4(2), 157-178. <https://doi.org/10.1108/JOEPP-03-2017-0022>
- van der Togt, J., & Rasmussen, T. H. (2017). Toward evidence-based HR. *Journal of Organizational Effectiveness*, 4(2), 127–132. <https://doi.org/10.1108/JOEPP-02-2017-0013>
- Verma, S., & Chaurasia, S. (2019). Understanding the determinants of big data analytics adoption. *Information Resources Management Journal*, 32(3), 1–26. <https://doi.org/10.4018/IRMJ.2019070101>
- Weam, T., Rana Abu, T., Mohammed, O., Yahya, S., Ramiz, A., Ali, B., Mohammad, K., Ruaa, B., Nidal, A., & Abdalmuttaleb, A.-S. (2023). Factors influencing adoption of HR analytics by individuals and organizations. *Information Sciences Letters*, 12(7), 3193–3204. <https://doi.org/10.18576/isl/120744>