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Understanding the Predictors of HR Analytics Uptake in Indian Corporate Enterprises

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Abstract: In the context of rapid digital transformation and data-driven decision-making, this study examines the key determinants influencing the adoption of Human Resource Analytics within corporate organizations in India. Grounded in the Technology Acceptance Model, the research investigates the role of technological readiness, organizational capabilities, environmental conditions, and internal motivational factors. A quantitative research design was employed, collecting data from 180 HR professionals across various Indian industries, and the proposed model was analyzed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The findings indicate that although the hypothesized relationships do not reach conventional levels of statistical significance, employee-related factors demonstrate a relatively stronger influence on intentions to adopt HR Analytics. These results suggest that HR Analytics adoption in India is still at an early stage, with growing emphasis on behavioral preparedness, skill development, and supportive organizational structures. The study contributes to the HR analytics literature by offering one of the first empirical investigations from an emerging economy context.

Keywords: Human Resource Analytics, Technology Adoption, Structural Equation Modelling, Organizational Competence, Technology Acceptance Model.

INTRODUCTION

The rising digitalization of organizations has brought about a paradigm shift in the role of Human Resource Management from an administrative support role to a strategic partner in decision-making. In this context, organizations are facing increasing pressure to use workforce data to improve efficiency, forecast talent outcomes, and align human capital strategy with business goals. This has led to the rise of Human Resource Analytics as an important capability that helps organizations make informed decisions using the analysis of employee data (Marler & Boudreau, 2022).

Human Resource Analytics is the use of statistical methods and tools of analysis and data-driven approaches to human resource data for the purpose of enhancing decisions related to the workforce. Through the integration of data from human resource information systems, enterprise resource planning systems, and digital workforce solutions, HR Analytics enables fundamental HR activities like recruitment, performance management, employee engagement, retention, and workforce planning (Boudreau & Ramstad, 2005; Chattopadhyay & Ghosh, 2020). There is empirical support for the view that organizations with superior analytics capabilities are better equipped to unlock insights that can lead to strategic outcomes (Marler & Boudreau, 2022).

Although the importance of HR Analytics has been well acknowledged, its adoption is still varied among different organizations. Although many organizations are able to generate a considerable amount of data regarding their workforce, only a small percentage of them are able to leverage this data and turn it into useful insights. It has been found in previous studies that most organizations are still in the initial stages of analytics maturity, mostly using descriptive analytics, and are yet to adopt predictive and prescriptive analytics (Ramachandran, 2023; Sakib, 2024).

These issues are more pronounced in the emerging economies, such as India. The Indian corporate enterprises function in a dynamic environment that is marked by fast growth, global competition, and a diverse workforce. Although Indian organizations generate substantial amounts of HR related data, several barriers hinder effective HR Analytics adoption, including inadequate technological infrastructure, data quality concerns, limited analytical skills, and difficulties in system integration (Dhamija & Bag, 2020; Bishnoi & Vikas, 2024). Moreover, cultural resistance to data-driven decision-making, a lack of support from top management, and misalignment between HR strategy and business goals also limit the adoption of analytics in HR departments (Chatterjee & Saini, 2020).

The implementation of HR Analytics is a multi-dimensional process that is affected by technology, organizational, environmental, and individual-level factors. Technology adoption models, especially the Technology Acceptance Model, highlight the importance of perceived usefulness and perceived ease of use as important antecedents of individual intention to use new technology (Davis, 1989). In the context of HR Analytics, individual-level perceptions are intertwined with organizational-level factors such as the availability of analytical tools and data, organizational competence, facilitating conditions, and strategic orientation, and environmental factors such as competitive intensity and industry standards (Tunsi et al., 2023; Ilyas et al., 2025). Empirical research that explores these multiple dimensions together in predicting the adoption of HR Analytics, particularly in the Indian corporate setting, is relatively scarce. With these research gaps in mind, the current study aims to explore the predictors of HR Analytics adoption in Indian corporate enterprises by empirically analyzing the role of technological availability, organizational competence, environmental forces, and individual-driven factors. By adopting a quantitative research approach and validating a multi-dimensional framework through Partial Least Squares Structural Equation Modeling, this research study aspires to make a meaningful contribution to the existing body of literature on HR Analytics by presenting context-specific empirical findings from an emerging economy. The results of this study are expected to provide theoretical as well as practical insights into HR Analytics adoption.

LITERATURE REVIEW

2.1 Concept and Evolution of Human Resource Analytics

Human Resource Analytics has emerged as a strategic approach that uses statistical, analytical, and data-driven methods to analyze human resource data to improve decision-making and organizational performance. The traditional approach to HR was more administrative, with a focus on record-keeping and compliance. However, the advancements in digital technology, data storage, and analytics have made it possible for HR functions to move towards a strategic approach (Marler & Boudreau, 2022).

Recent literature has defined HR Analytics as the application of workforce data to produce insights about employee recruitment, performance management, employee engagement, retention, and workforce planning (Boudreau & Ramstad, 2005). The increasing use of HR information systems and enterprise software has made it easier to produce data, but the application of this data to produce insights is still a challenge (Ramachandran, 2023). This indicates the need to understand the factors that influence the adoption of HR Analytics.

2.2 Theoretical Foundations of HR Analytics Adoption

The literature on technology adoption offers a robust theoretical basis for studying the adoption of HR Analytics. Various models, such as the Technology Acceptance Model, Unified Theory of Acceptance and Use of Technology, Technology–Organization–Environment framework, and Resource-Based View, have been extensively used to explain adoption behavior (Davis, 1989; Venkatesh et al., 2003).

The empirical study by **Tunsi et al. (2023)** adopts the UTAUT framework to examine both individual and organizational adoption of HR Analytics. Their findings emphasize that performance expectancy, effort expectancy, self-efficacy, data availability, and resource availability significantly influence adoption intentions, while fear appeals show no significant effect. This indicates that HR Analytics adoption is largely driven by perceived capability and performance enhancement rather than threat-based motivations. Complementing this, the systematic review by Sindhuja and Dunstan (2024) synthesizes HR Analytics adoption literature using the TCCM framework and identifies dominant theoretical lenses such as RBV, TOE, diffusion of innovation, and social-technical systems theory. Their review highlights that adoption is a multidimensional phenomenon influenced by technological readiness, organizational competence, environmental pressures, and human factors. Technological readiness is an important factor in the adoption of HR Analytics. Data availability and system integration are basic prerequisites for any analytics project. This is supported by Tunsi et al. (2023), who empirically proved that data availability is a major factor in the acceptance of HR Analytics at both individual and organizational levels, and that fragmented data systems are a barrier to analytics adoption.

Similarly, Sindhuja and Dunstan (2024) identify technological infrastructure, analytics tools, and data quality as recurring facilitators and barriers across studies. Organizations with integrated HRIS, compatible IT systems, and advanced analytical tools exhibit higher readiness for HR Analytics adoption. In contrast, poor data governance, lack of interoperability, and outdated systems impede analytics maturity. Organizational competence, such as top management support, strategic alignment, and facilitating conditions, plays an important role in the adoption of HR Analytics. It has been found in previous research that top management support helps in increasing investment in analytics infrastructure and helps in creating a data-driven culture (Chatterjee & Ghosh, 2020).

Sindhuja and Dunstan (2024) report that organizations operating in competitive and technology-intensive environments are more inclined to adopt HR Analytics to gain strategic advantage. However, adoption remains uneven across industries and organizational sizes, particularly in emerging economies where resource constraints are prominent. Individual level factors are repeatedly identified as critical determinants of HR Analytics uptake. Tunsi et al. (2023) find self-efficacy and quantitative self-efficacy to be among the strongest predictors of adoption. HR professionals who perceive themselves as capable of handling analytical tools and quantitative tasks are more likely to accept and use HR Analytics. The systematic review further reveals that resistance to change, lack of analytical skills, and limited training opportunities restrict adoption despite organizational investments (Sindhuja & Dunstan, 2024). These findings suggest that HR Analytics adoption is not solely a technological or structural issue but also a behavioral and capability-driven process.

2.3 Research Gap and Rationale

Notwithstanding the increasing literature on HR Analytics, there are still some gaps that emerge. Firstly, while individual, organizational, and technological variables have been explored separately, there is a lack of empirical work that combines these variables in one validated model, especially in emerging economies.

Second, the systematic review by Sindhuja and Dunstan (2024) points out that, although India is a prominent country in the context of HR Analytics studies, the majority of the literature is either descriptive in nature or provides industry-specific information. There is a requirement for quantitative research that uses effective analytical tools like PLS-SEM to investigate the factors influencing adoption.

Third, empirical evidence shows that the adoption of HR Analytics is in the early stages, with mixed and sometimes non-significant results, reflecting changing patterns of adoption (Tunsi et al., 2023). It is important to understand these early stages of adoption to advance theory and practice.

To address these research gaps, this study proposes and tests a multidimensional model that includes technological availability, organizational competence, environmental forces, and individual driven factors to explain HR Analytics adoption in Indian corporate enterprises

2.4 Conceptual Model and Hypotheses Development

Based on existing theories of technology adoption and existing empirical studies, this study proposes a conceptual framework to investigate the factors that influence the adoption of HR Analytics in organizations. The framework is derived from the synthesis of existing literature and fundamental studies on HR

Analytics adoption, which highlight the complex nature of adoption behavior. The proposed conceptual framework identifies HR Analytics adoption as being shaped by four higher-order constructs, namely technology availability, organizational competence, environmental forces, and individual-driven factors. These constructs represent critical dimensions that collectively shape organizational readiness and intention to adopt HR Analytics, particularly in the pre-implementation stage. Figure 1 presents the conceptual model of the study.

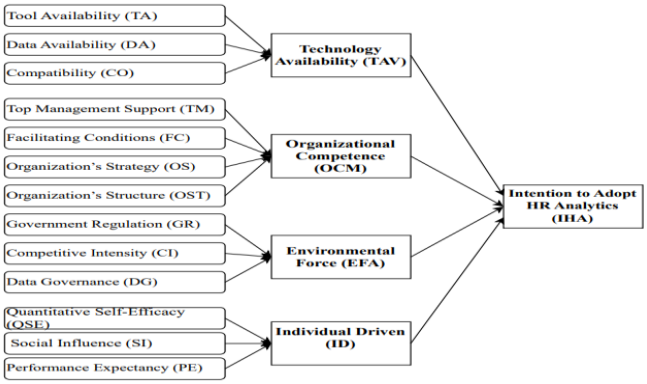

Figure 1: Conceptual Model

Together, these four dimensions offer a holistic explanation of the adoption of HR Analytics by combining technological, organizational, environmental, and individual factors. On the basis of the conceptual framework, the following hypotheses are proposed:

H1: The availability of technology has an impact on the adoption of HR Analytics.

H2: Organizational competence has an effect on HR Analytics adoption.

H3: There is an impact of environmental forces on the adoption of HR Analytics.

H4: There is an effect of individual-driven factors on the adoption of HR Analytics.

2.5 Research Objectives

1. To determine and analyze the major factors that impact the adoption of Human Resource Analytics in Indian corporate enterprises.

This objective is centered on the systematic investigation of the organizational, technological, environmental, and employee-related determinants that influence or impede the adoption of HR Analytics. Through the empirical analysis of these determinants, the research aims to transcend the boundaries of conceptual debates and develop an evidence-based understanding of what shapes the adoption of HR Analytics in the Indian corporate context.

2. To analyze the extent to which organizational, technological, environmental, and human factors influence the degree and effectiveness of adoption of HR Analytics in Indian organizations.

The purpose of this objective is to evaluate the relative importance and weight of these factors using quantitative analysis. It attempts to evaluate the impact of these factors together and individually on the implementation and use of HR Analytics, and hence provide an insight into the success of its adoption.

3. RESEARCH METHODOLOGY

3.1 Research Design

The current study uses a quantitative, explanatory, and cross-sectional research design to explore the factors influencing the adoption of HR Analytics in organizations. The survey method was used in this study since it allows for the systematic assessment of the relationship between a number of latent variables and is useful for testing a conceptual framework. This research design is applicable when exploring adoption intentions at the pre-implementation phase, where perceptual and readiness factors are important.

3.2 Population and Unit of Analysis

The target population for the study includes HR professionals, managers, and executives working in Indian corporate organizations. The respondents were deemed appropriate since they are directly or indirectly involved in HR decision-making processes, digital HR initiatives, and analytics-related activities. The unit of analysis for the study is the organization, and the responses are collected at the individual level to determine the readiness and intention to adopt HR Analytics.

3.3 The sampling technique

A non-probability purposive sampling method was used to ensure that the respondents had sufficient exposure to HR practices, HR information systems, or analytics-related initiatives in their organizations. The sampling method is often used in technology adoption research, where knowledge of the domain is necessary.

The data was collected from 180 HR professionals. The sample size was considered sufficient for the Partial Least Squares Structural Equation Modelling analysis, as it is appropriate for complex models and medium-sized samples. The study satisfies the guidelines for the minimum sample size requirements for PLS-SEM analysis based on the complexity of the model.

3.4 Instrument Development and Measurement

Data were collected using a structured questionnaire developed by adapting validated scales from prior technology adoption and HR Analytics literature. The measurement model was specified as a hierarchical component model, wherein higher-order constructs were operationalized through theoretically grounded lower-order dimensions. Technology Availability was measured using tool availability, data availability, and system compatibility, adapted from technology acceptance and diffusion studies (Venkatesh et al., 2003; Johnston, 2006; Rogers, 2003). Organizational Competence was operationalized through top management support, facilitating conditions, organizational strategy, and organizational structure (Kamal, 2006; Venkatesh et al., 2003; Saraswathy et al., 2017; Fiocco, 2017). Environmental Forces comprised government regulation, competitive intensity, and data governance, adapted from prior studies on environmental and regulatory influences on technology adoption (Zhu & Kraemer, 2005; Zheng, 2014; Ladley, 2012). Individual-Driven Factors included quantitative self-efficacy, social influence, and performance expectancy, grounded in UTAUT and self-efficacy literature (Davis, 1989; Venkatesh et al., 2003; Ozgen, 2013). Intention to Adopt HR Analytics was measured using pre-adoption intention items adapted from established technology adoption scales (Venkatesh et al., 2003; Hameed et al., 2012).

All items were measured using 5-point Likert scales, ranging from strong disagreement to strong agreement. Minor contextual modifications were made to ensure relevance to the HR Analytics context while preserving scale validity.

3.5 Data Collection Procedure

Primary data were collected through an online survey administered to HR professionals across Indian corporate enterprises. The online mode facilitated wider geographical reach and timely responses from participants. Respondents were informed about the academic purpose of the study, and participation was entirely voluntary. Anonymity and confidentiality of responses were assured to reduce response bias and encourage honest reporting.

3.6 Data Analysis Technique

The collected data was analyzed through Partial Least Squares Structural Equation Modelling (PLS-SEM). The choice of PLS-SEM was based on its appropriateness for use in exploratory and predictive research, handling complex models with multiple constructs, and its robustness with small to moderate sample sizes.

The analysis consisted of a two-step procedure. First, the measurement model was evaluated to test the indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. Second, the structural model was evaluated to test the proposed relationships among the constructs, including the path coefficients, significance levels, and fit of the model.

4. RESULT AND ANALYSIS

This section reports the findings from the empirical study that was carried out using Partial Least Squares Structural Equation Modelling (PLS-SEM). The study was done in two phases. First, the measurement model was tested to ensure construct reliability and validity. Then, the structural model was tested to determine the proposed relationships between the constructs that shape the adoption of HR Analytics.

The demographic representation of the respondents (Table 1) gives an insight into the characteristics of the sample and helps to determine the appropriateness of the data for analyzing the adoption of HR Analytics. A total of 180 responses were considered for analysis. The largest proportion of respondents were female (45.83 percent), followed by male respondents (37.50 percent), while 16.67 percent chose not to answer the question about their gender. With respect to age, the largest proportion of respondents were in the 18-27 years and 28-43 years age groups, which indicates that the majority of the respondents are early- and mid-career professionals. In relation to the educational background of the respondents, the majority were graduates, followed by postgraduates, while the remaining were from the senior secondary and doctoral groups.

Table 1: Demographic Profile

Variable	Category	Frequency	Percentage
Gender	Male	45	37.5
	Female	55	45.83
	Prefer not to say	20	16.67
Age Group	18–27 years	50	41.67
	28–43 years	40	33.33
	44–59 years	25	20.83
	Above 60 years	5	4.17
Educational Background	Senior Secondary	20	16.67
	Graduate	60	50
	Post Graduate	30	25
	Doctorate	10	8.33

4.1 Assessment of the Measurement Model

The results of the measurement model were analyzed to determine the reliability of the indicators, internal consistency reliability, convergent validity, and discriminant validity, following the guidelines for evaluating PLS-SEM results (Hair et al., 2017; Hair et al., 2019). The results for the reliability of the indicators, internal consistency reliability, and convergent validity of the constructs in the study are shown in Table 2. The discriminant validity was then tested using the Fornell-Larcker criterion, and the results are shown in Tables 3 and 4.

4.1.1 Indicator Reliability

The reliability of the indicators was checked by the outer loadings of the measurement items on the constructs. The majority of the indicators showed loadings above the recommended threshold of 0.70, indicating that the indicators adequately represented the latent constructs.

latent constructs (Hair et al., 2017). Some indicators had marginally lower loadings; however, these items were kept as they helped in content validity and did not impact the values of composite reliability adversely (Hair et al., 2019).

Table 2: Indicator Reliability, Internal Consistency Reliability, and Convergent Validity of the Measurement Model

Construct	Cronbach's alpha	(rho_a)	(rho_c)	(AVE)
CI	0.495	0.514	0.752	0.510
CO	0.592	0.648	0.781	0.551
DA	0.590	0.594	0.784	0.547
DG	0.661	0.659	0.816	0.598
FC	0.666	0.671	0.817	0.599
GR	0.541	0.538	0.765	0.522
IA	0.551	0.588	0.769	0.532
OS	0.626	0.635	0.801	0.574
QSE	0.638	0.632	0.803	0.576
SI	0.760	0.808	0.861	0.677
TA	0.740	0.794	0.851	0.660
TM	0.610	0.665	0.780	0.545
EFA	0.731	0.770	0.845	0.647
ID	0.837	0.887	0.899	0.748
OCM	0.803	0.821	0.870	0.626
TAV	0.757	0.823	0.861	0.675

4.1.2 Internal Consistency Reliability

The internal consistency reliability of the measurement model was evaluated using Cronbach's alpha and composite reliability. While a few constructs had Cronbach's alpha values slightly lower than the recommended threshold, these are acceptable in exploratory studies and research involving new constructs (Hair et al., 2017). More importantly, the composite reliability values of all constructs were above the recommended minimum of 0.70, ensuring that the internal consistency of the measurement model was satisfactory (Hair et al., 2019).

4.1.3 Convergent Validity

Convergent validity was evaluated through the Average Variance Extracted (AVE). The AVE of all constructs was found to be above the recommended threshold of 0.50, which means that all constructs explained more than half of the variance in their indicators (Fornell & Larcker, 1981; Hair et al., 2017). These findings further support that the measurement model has adequate convergent validity.

4.1.4 Discriminant Validity

The discriminant validity was checked using the Fornell-Larcker criterion, which is still a widely accepted method in the PLS-SSEM procedure for checking the uniqueness of constructs (Fornell & Larcker, 1981; Hair et al., 2017). The Fornell-Larcker criterion states that if the square root of the Average Variance Extracted is greater than the correlation between constructs, then the discriminant validity is established.

Tables 3 and 4 below show the Fornell-Larcker criteria values for the lower-order and higher-order constructs, respectively. As can be seen from the tables, the square root of the AVE (values along the diagonal) for each construct is greater than the correlation between the constructs. This implies that for each construct, there is more variance shared with its indicators than with the other constructs in the model. Based on these findings, it can be concluded that there is adequate discriminant validity, and the constructs in the measurement model are empirically distinct.

Table 3: Fornell Larcker Criterion of Higher Order Construct

Construct	EFA	ID	IHA	OCM	TAV
EFA	0.804				
ID	0.573	0.865			
IHA	0.634	0.464	1.000		
OCM	0.793	0.576	0.587	0.791	
TAV	0.619	0.531	0.554	0.711	0.822

Table 4: Fornell-Larcker criterion of Lower Order Construct

Construct	CI	CO	DA	DG	EFA	FC	GR	IA	ID	OCM	OS	OST	PE	QSE	SI
CI	0.714														
CO	0.411	0.742													
DA	0.493	0.499	0.740												
DG	0.483	0.520	0.545	0.773											
EFA	0.751	0.545	0.570	0.865	0.593										
FC	0.425	0.438	0.668	0.603	0.618	0.774									
GR	0.410	0.375	0.327	0.533	0.798	0.438	0.722								
IA	0.358	0.374	0.572	0.599	0.632	0.530	0.531	0.729							
ID	0.597	0.500	0.379	0.452	0.586	0.406	0.391	0.435	0.697						
OCM	0.661	0.586	0.631	0.709	0.805	0.814	0.569	0.582	0.591	0.599					
OS	0.733	0.434	0.459	0.482	0.626	0.368	0.331	0.361	0.623	0.743	0.758				
OST	0.547	0.605	0.498	0.625	0.709	0.538	0.535	0.529	0.496	0.795	0.510	0.772			
PE	0.497	0.420	0.298	0.371	0.465	0.295	0.265	0.370	0.911	0.516	0.597	0.461	0.826		
QSE	0.444	0.359	0.291	0.389	0.518	0.363	0.436	0.494	0.810	0.463	0.347	0.457	0.621	0.759	
SI	0.610	0.516	0.396	0.420	0.554	0.408	0.340	0.292	0.882	0.557	0.649	0.381	0.721	0.553	0.823
TA	0.568	0.355	0.676	0.354	0.449	0.474	0.189	0.382	0.520	0.528	0.508	0.326	0.420	0.440	0.500
TAV	0.601	0.698	0.899	0.572	0.631	0.647	0.352	0.552	0.560	0.703	0.568	0.561	0.456	0.441	0.563
TM	0.405	0.372	0.354	0.520	0.587	0.632	0.479	0.398	0.362	0.818	0.528	0.451	0.302	0.300	0.340

4.2 Assessment of the Structural Model

After establishing the adequacy of the measurement model, the structural model was assessed to test the hypothesized relationships between technology availability, organizational competence, environmental forces, individual-driven factors, and HR Analytics adoption, using PLS-SEM. Figure 2 presents the structural model illustrating the proposed relationships among the constructs.

The measurement model was sufficient, we assessed the structural model using PLS-SEM to explore the proposed relationships among technology availability, organizational competence, environmental forces, individual-driven factors, and HR Analytics adoption. This assessment in PLS-SEM involved examining the path coefficients to identify the magnitude and direction of the relationships between the constructs. We tested the significance of these paths with the bootstrapping procedure in PLS-SEM. Additionally, we evaluated the model's explanatory power through the coefficient of determination (R^2) to see how well the independent variables explained the variance in HR Analytics adoption. We also looked at effect sizes (f^2) and predictive relevance (Q^2) to gauge the contribution and predictive ability of each exogenous construct. Figure 2 shows the structural model is created, highlighting the proposed relationships among the study variables.

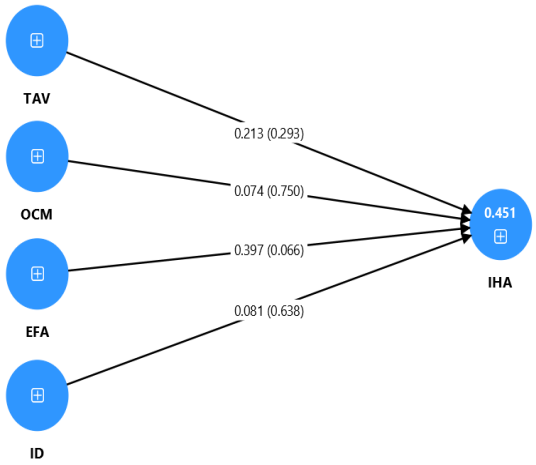

Figure 2: Structural Model of the Construct

4.2.1 Path Coefficients and Hypothesis Testing

The structural model results indicate that none of the hypothesized relationships achieved statistical significance at the conventional 5 percent level. Among the examined paths, the relationship between individual-driven factors and HR Analytics adoption exhibited the highest path coefficient, indicating a relatively stronger influence compared to other constructs, although it remained marginally insignificant. The paths from technology availability, organizational competence, and environmental forces to HR Analytics adoption showed positive but weak coefficients, suggesting that while these factors contribute to adoption readiness, their influence may not yet be strong enough.

5. FINDINGS AND CONCLUSION

5.1 Findings

Objective 1: To determine and analyze the major factors that impact the adoption of Human Resource Analytics in Indian corporate enterprises

environmental, and human factors collectively influence HR Analytics adoption; however, their impact varies in strength. Technology availability, organizational competence, and environmental forces show positive but statistically insignificant effects, indicating that while these factors are present, they are not yet strong enough to independently drive adoption. Among the identified factors, individual-driven factors, including quantitative self-efficacy, social influence, and performance expectancy, emerge as relatively more influential, highlighting the need of human readiness in the early stages of adoption of HR Analytics.

Objective 2: To analyze the extent to which organizational, technological, environmental, and human factors influence the degree and effectiveness of adoption of HR Analytics in Indian organizations

The findings suggest that the net effect of organizational, technological, and environmental variables on the adoption of HR Analytics is still limited, which is an indication of the emerging nature of analytics adoption in Indian corporate enterprises. While the organizations have basic readiness in terms of infrastructure, management support, and awareness, this has not yet resulted in effective adoption. However, human factors have a relatively stronger impact, which indicates that individual capability, confidence in analytics use, and performance benefits have a crucial role in influencing adoption intention and effectiveness.

5.2 Conclusion

This research work offers empirical insights into the factors that influence the adoption of HR Analytics in Indian corporate enterprises by considering the technological, organizational, environmental, and human factors in a unified manner. The results show that the adoption of HR Analytics is in its nascent stage, where the adoption efforts are not adequately fueled by structural and external factors. Rather, the individual-level factors associated with skills, self-efficacy, and perceived usefulness seem to play a more pivotal role in shaping the adoption intention. This research work makes an original contribution to the burgeoning body of knowledge on HR Analytics by presenting country-specific insights from an emerging economy.

6. LIMITATIONS AND FUTURE SCOPE

However, the study has some limitations that need to be kept in mind while analyzing the results. First, the cross-sectional research design limits the ability to measure the dynamics of HR Analytics adoption. Second, the study is based on self-reported data, which may cause response bias despite the assurance of anonymity. Third, although the sample size is appropriate for PLS-SEM analysis, it is not generalizable to all industries.

Future studies could consider these limitations by using longitudinal research methodologies to study the dynamics of HR Analytics adoption. Research could also be conducted on sector-level or size-level analyses to derive more insights. Moreover, using objective performance measures and analyzing outcomes post-adoption could also add more value to the understanding of the effectiveness and maturity level of HR Analytics adoption.

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