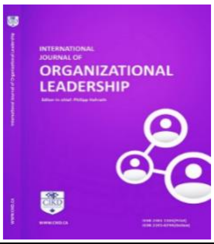

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Exploring the Adoption of Human Resource Analytics among Human Resource Professionals

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Abstract

Human Resource (HR) analytics is emerging as a must-have capability for organisations. The readiness of HR professionals is vital for implementing HR analytics. This paper aims to understand the adoption of HR analytics among HR professionals. The authors empirically explored the adoption of HR analytics by applying the Unified Theory of Acceptance and Use of Technology (UTAUT), a prominent technology adoption model developed by Venkatesh et al. (2003). HR professionals from various industries were approached to study the variables of technology adoption in light of HR analytics. This paper aims to understand the adoption of HR analytics among HR professionals. HR professionals from various industries were approached to study the variables of technology adoption in light of HR analytics. The study's findings show a significant relationship between performance expectancy, social influence, and facilitating conditions on the adoption of HR analytics among HR professionals. Effort expectancy has no substantial relation to adopting HR analytics among HR professionals. This paper brings out implications from the research towards the adoption of HR analytics. Senior managers need to guide HR professionals, and organisations must create the necessary infrastructure to enable HR professionals to adopt HR analytics. This paper assumes value by providing insights into the approaches to be followed by organisations towards the speedy adoption of HR analytics by HR professionals.

Sophisticated technologies have entered into the measurement of Human Resource (HR) activities. Organizations are now interested in focusing exclusively on HR data and applying analytics in the HR domain. Attention towards measuring HR data has resulted in the emergence of a new field of HR analytics. Leading companies are using sophisticated and advanced data analytics to enhance their human resource value. The growth of data-related technology is what's driving the rising interest (Merkle & Steinman, 2021). Companies are giving up guesswork in people management issues. They are instead attempting to leverage data analytics to help to improve various talent management functions. Beyond this, they are using human resource analytics as a driver for business performance and an important differentiator from competitors. The contribution of HR is not just limited to functional activities but has expanded to generate financial output (Mohammed, 2019). Organizations are gauging HR analytics in terms of the Return on Investment (RoI) accumulated through its implementation (Chalutz Ben-Gal, 2019). HR Analytics provides organizations with a comprehensive analysis of various HR programs being executed by the organization. Increased storage capabilities and the emergence of 'Big Data' has given the impetus to the growth of this domain. The demand for HR Analytics at the workplace has never been so high as in recent times. Also, organizations are heralding that human resources are the critical capital that they must bank upon (Lahey, 2014). As the people, processes, and systems mature, HR analytics is bound to grow in its potential and has an enormous scope to become a cliché for any organization. People analytics is in its infancy as a discipline since it lies at the confluence of business analytics and HR. Technology is also improving to meet the expectations of organizations and deliver the desired results that have been a long wait (Isson & Harriott, 2016). The field of HR analytics goes under a few distinct names, including human capital analytics, talent analytics, people analytics, and workforce analytics. However, the concept of HR analytics can be understood to be the same regardless of the phrase used. HR analytics is an advanced level of going beyond traditional HR metrics. HR analytics provides data-driven insights that enable HR professionals and top managers to make effective, long-term, strategic decisions about their human resources (Fecheyr-Lippens et al., 2015). Because of the tremendous applications that may be achieved through predictive analytics, HR analytics is getting growing recognition.

The Backdrop of HR Analytics

The beginnings of HR analytics can be seen in the late 1960s. The efforts of American Airlines Sabre to launch its reservation system marked the beginning of the application of analytics to the process of making business decisions, even though it was not as well-known at the time in the field of HR (Fitz-enz & Mattox, 2014). Jac Fitz-enz developed 30 HR metrics to assess human resource functions during subtle phases of data expansion. In 1989, Fitz-enz collaborated on the creation of these measures with the Saratoga Institute and the American Society for Personnel Administration (ASPA). ASPA later evolved into the modern-day Society for Human Resource Management (SHRM). It's possible that at this point, the first theoretical underpinnings of assessing human resource operations began, which later took on an analytical form.

Benchmarking was commonly used in the 1990s to measure HR function growth till the early 2000s. Kaplan and Norton (1996) invented the Balanced Score Card (BSC) to measure company performance and other functions (Kaplan & Norton, 2001). By the 1990s and early 2000s, BSC was widespread throughout sectors. "HR Score Card" by Becker et al. (2001) linked HR operations to corporate strategies. This relationship improved organisational outcomes. Michael Lewis' (2004) work Moneyball, about Billy Beane's player selection approach, highlighted analytics' predictive power (Soundararajan & Singh, 2017). Google started "Project Oxygen" in 2009 to use data and intelligence to identify good managers. This marked a major corporation's push to use HR analytics. HR analytics was once limited to reporting and measurements. Leading companies started using predictive analytics in HR around 2010 (Davenport et al., 2010).

For the past decade, organisations have had a great deal of data. Data availability has improved as all companies adopted technology and developed sophisticated HR Information systems. Companies have learned that studying this data and using the results will elevate the role of HR. HR Analytics has grown into its own area from its roots in business analytics. Numerous corporate HR leaders and experts have advised HR to use analytical skills to become a data-driven decision influencer. HR may significantly impact corporate outcomes, as shown by several studies (Roehling et al., 2005).

HR analytics is gaining acceptance, but professionals must be ready to manage analytics functions to succeed. Field studies contradict professional readiness. For a long time, the industry is anticipated to face a shortage of skilled technologists and analysts (Fitz-enz & Mattox, 2014). Globally, 65% of workers working in a strong HR analytics culture influenced corporate performance, according to a CIPD (2018) report. This emphasises the need to promote a people-analytics-friendly culture. Human resource management needs HR analytics to become an evidence-based profession (CIPD, 2018). HR specialists with strong analytics skills are more likely to be promoted and recognised by top management (Sinar, 2018).

In the 2017-Sierra-Cedar survey (2016-2017), which completed 20 years of evaluating HR system adoption, the percentage of firms formally doing Business Intelligence (BI)/HR analytics remained steady. The survey indicated that BI software improved overall, but talent management applications did not. Deloitte (2018) tracks global HR trends annually. The 2018 Deloitte Global Human Capital trend reports found that 84% of respondents valued HR analytics. People analytics focused on crucial workforce concerns in 2018. Around 70% of organisations implemented substantial decision-making analysis and integration programmes.

HR professionals must have analytical skills to use HR analytics in their work (Kalvakolanu et al., 2019). According to trends, many companies are implementing HR analytics. Academics are increasingly interested in HR analytics, and business organisations are similarly enthusiastic about the field's potential (Qamar & Samad, 2022). Yet, how well HR professionals use HR analytics information is important. In this context, the present study examines HR professionals' readiness towards HR analytics adoption.

Review of Literature and Hypothesis Development

HR analytics synthesizes business analytics and human resources. As an emerging area, HR analytics is not yet fully explored. Research in this area is gradually building up. In this section, a condensed version of the literature review that was done in preparation for the study is offered.

Malladi and Krishnan (2013) examined business intelligence and analytics drivers in a wide sample of organisations. The study used TOE (Technological-Organizational-Environmental) framework. BIA (Business Intelligence and Analytics) utilisation was ordered to provide a summative index of organisational business activity BIA usage. Malladi (2013) studied contextual factors that may affect corporate intelligence and analytics system installation using TOE framework. The study found that industry standards and knowledge intensity may affect business intelligence and analytics adoption. This implies that HR analytics adoption and implementation may increase industry knowledge requirements for HR practitioners.

Falletta (2014) surveyed 3,000 HR professionals using 29 core items. Half (49.5%) of the organisations studied said that HR analytics was not fundamental to HR strategy creation. HR professionals may assess data and explain predictive insights in individual, group, and organisational behavioural contexts.

In their study of 302 HR professionals, Vargas (2015) compared the business's aim to employ HR analytics to HR professionals' preparedness to adopt and use it for the business's benefit. This study applied Venkatesh et al. (2003)'s Unified Theory of Acceptance and Use of Technology (UTAUT) paradigm. The study found that existing technologies support HR practitioners' usage of HR analytics.

In their study, Van den Heuvel and Bondarouk (2017) qualitatively assessed Dutch HR analytics practitioners' future expectations. Twenty participants were studied using the analytical hierarchy method. HR analytics was examined as of 2015 and projected for 2025. The study found that manyHR professionals dedicate a great deal of effort to basic reporting and metrics computation for HR analytics.

Chahtalkhi (2016) identified corporate challenges while implementing new programmes like HR analytics. For the study, HR analytics employees from three firms provided qualitative data. This study depicted HR analytics as an organisational change programme. The study emphasised that HR professionals must first understand data and statistics.

Angrave et al. (2016) argued that HR practitioners must integrate analytics to play the most strategic HR role. The authors examined big data and HR analytics theories and discussed HR analytics implementation barriers. Their study found that HR practitioners lack analytical thinking, which hinders HR analytics growth and implementation.

Kaur and Fink (2017) studied "Trends and Practices in Talent Analytics" to understand talent (HR) analytics practises. HR analytics experts require abilities in statistical analysis, study design, visualisation, narrative, survey design, and exploratory analysis.

In a qualitative study employing various case studies, Ruohonen (2015) examined how firms use predictive analytics in HR. All firms struggled to find predictive analytics and HR business process experts. The study's respondents valued HR professionals' analytical skills.

Jensen-Eriksen (2016) used bottom-up inductive reasoning to draw conclusions from evidence and develop a theory for better understanding. Textual analytics was employed to examine HR analytics data from 510 HR professional blogs and communities. As per the study, data-driven HRM requires human judgement from HR experts.

Marler and Boudreau (2016) meta-analyzed HR Analytics reviews. They examined numerous HR analytics works to demonstrate progress. The study found that many firms lacked analytical HR personnel. HR analytics require improved HR information technology, according to organisations.

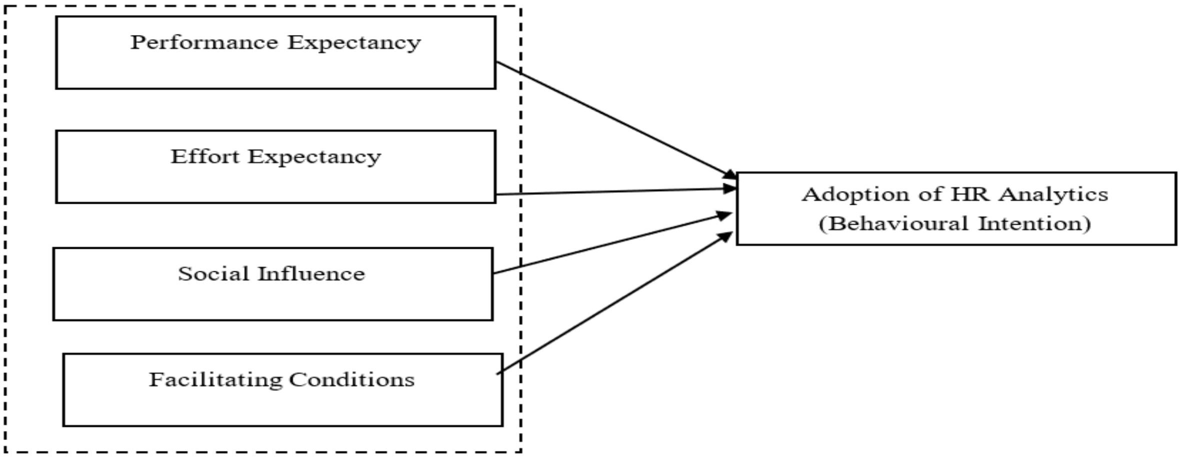
Lismont et al. (2017) examined analytic maturity descriptively using the DELTA model. They examined the organisations in five dimensions, which uncovered many untapped HR analytics opportunities. Recent analytics adopters have little used HR analytics. HR analytics is not universal. Innovative and long-term analytics implementers can only advance this. Data quality matters. With accurate data, HR analytics can acquire popularity (Lismont et al., 2017).

As HR analytics is a comparatively new technology, how far the HR professionals are ready to accept the technology is to be assessed. A number of researchers have also emphasized the need to study the adoption of HR analytics among HR professionals. The adoption of HR analytics is essential for HR professionals to remain competitive and relevant in the future (Vargas et al., 2018). Besides that, HR professionals need to develop their analytical skills in order to be able to effectively use HR analytics (Marler & Boudreau, 2017). A number of studies have highlighted the need to study the adoption of HR analytics among HR professionals. Khan et al. (2023) found that performance expectancy, effort expectancy, resource availability, quantitative self-efficacy, data availability, and social influence are the most significant factors positively influencing individual acceptance and adoption of HR analytics. Alrasheedi (2023), found that the adoption of HR analytics is still low in Saudi Arabia, with only 36.42% of the respondents working in the employee relations functional area within the HR department reporting to use HR analytics. The study also found that the lack of awareness of HR analytics and the lack of support from senior management are the main barriers to adoption.

According to the evaluation of the relevant literature, there is a deficiency in the research about the readiness of HR experts to accept and make use of HR analytics. In the context of Indian HR professionals, it forms a critical factor to be studied. In the current study, an effort is made to gain an understanding of the degree to which human resource professionals are thinking about using HR analytics. The term "HR analytics" refers to an applied subfield of "business analytics," which is derived from "information technology". A brief review of various technology adoption models was carried out for this purpose. Technology adoption and usage has been widely studied in the present digital age. Over time, several models have emerged in technology adoption. The individual-level adoption has been extensively studied using the Technology Acceptance Model (TAM) by Davis (1989), the Theory of Planned Behavior (TPB) by Ajzen (1991), and the UTAUT developed by Venkatesh et al. (2003) (Oliveira & Martins, 2011). Among these technology adoption theoretical models, the UTAUT model (Venkatesh et al., 2003) has gained a prominent place. Venkatesh et al. (2003) reviewed the existing research in the field of technology adoption. By combining other models from social psychology and innovation research, they proposed the UTAUT model. In the present paper, the core idea of the adoption of HR analytics is studied using the UTAUT model. Among the theories and models that promulgated technology adoption at the individual level, UTAUT has brought together the essence of several former theories, particularly about information systems, and presented effort expectancy, performance expectancy, social influence, and facilitating conditions as four important constructs leading to individual-level adoption of technology (Taherdoost, 2018). As per the propositions of UTAUT, users' behavioural intention, and usage are dependent on four important variables (performance expectancy, effort expectancy, social influence, and facilitating conditions). The four variables are exposure to gender, age, experience, and voluntariness of use with moderating effects. UTAUT, as presented initially by Venkatesh et al. (2003). The UTAUT model is utilised in this research in order to investigate the attitudes of HR professionals toward the implementation of HR analytics. The model's variables have been validated multiple times to ensure that they accurately predict people's intentions towards their actions. UTAUT model is developed on the premise that performance expectancy, effort expectancy, social influence, and facilitating conditions are useful in identifying the behavioral intention of users towards a technology. These four variables lead to projecting the behavioral intention (adoption) of the user to use such information technology. The conceptual framework for the current study is presented in Figure 1.

Figure 1

Framework of Study on the Adoption of HR Analytics



Source: UTAUT (Venkatesh et al., 2003), Vargas (2015)

Research Question

What is the effect of performance expectancy, effort expectancy, social influence, and facilitating conditions on the adoption (behavioral intention) of HR analytics among HR professionals?

Research Objective

The main objective of the present study is to study the adoption of HR analytics among HR professionals. UTAUT (Venkatesh et al., 2003) and UTAUT2 (Venkatesh et al., 2012) are known for their usefulness in assessing the technology adoption in IT domain as well as several other consumer-related technology adoptions. The facilitating conditions are extensively studied in both these models and the studies based on them. It should be noted that in the conceptual framework that was used for the current study, some authors have preferred to use facilitating conditions as a variable to have a direct impact on use behaviour rather than behavioural intention. The factors in the surroundings of the workplace are proven to directly influence behavioural intention in the technology adoption context (Venkatesh et al., 2003; Venkateshet al., 2012). Under the HR analytics arena, facilitating conditions can be resources – human, technical, and other forms of support for HR analytics. Adequacy of the required tools and resources as facilitating conditions may motivate individuals to positively adopt new technology such as HR analytics. This is something that should be taken into consideration when analysing the results of this research. In the present study, the direct effect of facilitating conditions on behavioral intention (adoption) is being studied and not on the use behavior directly.

Hypotheses

The following hypotheses are proposed to fulfill the research objective.

H_1: Adoption of HR analytics is significantly influenced by performance expectancy

H_2: Adoption of HR analytics is significantly influenced by effort expectancy

H_3: Adoption of HR analytics is significantly influenced by social influence

H_4: Adoption of HR analytics is significantly influenced by facilitating conditions

H_5: There are differences in the adoption of HR analytics by gender

H_6: There are differences in the adoption of HR analytics by age

H_7: There are differences in the adoption of HR analytics by work experience

Method

Sample and Data Collection

The study collected primary data by serving the questionnaire to HR professionals across India. For the present study, non-probability sampling was considered. Purposive sampling was used to reach the HR professionals to be included in the study by keeping in view the need to reach the population with specific characteristics. As all HR professionals cannot be reached directly, a variant of the chain-referral sampling technique is used through professional networking sites. The questionnaire was served to a sample of about 900 HR professionals through a web link. HR analytics requires employee data of considerable size to show effective results. Hence, organizations with a total employee strength of more than 500 are considered for the population criteria. In total, 580 responses were received from the respondents. Incomplete responses and those who did not meet the required population criteria were eliminated. Finally, 390 responses were taken into consideration and analyzed for the present study.

Instruments

In order to collect the responses from HR experts with regard to the use of HR analytics, a structured questionnaire was developed. The framework of the study was applied to the questionnaire in the manner described, and a comparison was made between the attitudes of HR professionals regarding HR analytics and the use of HR analytics. As the questionnaire has been adapted from Venkatesh et al. (2003), further exploratory factor analysis was not done. The questionnaire was tested for validity and reliability before being administered to the respondents. It was determined whether the constructs used in the investigation were practically valid by taking the expert opinion involving practicing HR professionals. The instrument was tested on a small sample of 37 respondents and it was satisfactorily reaching the reliability norms, as indicated in Table 1. HR analytics is considered as technology in the present study. The constructs, performance expectancy, effort expectancy, social influence, and facilitating conditions influence the behavioral intention to use the technology (adoption of HR analytics in the present study) (Venkatesh et al., 2003). Performance expectancy reflects the extent to which new technology seems to be beneficial to the users for the completion of tasks. Effort expectancy reflects an individual’s feeling about the comfort or easiness of using a system. An individual's understanding of how the group relates and maintains certain values and beliefs with the members is considered a social influence. Facilitating conditions are the elements in one's environment that help the individual easily complete the task. Readiness to accept the new technology is indicated by behavioural intention. Constructs have been defined as per Venkatesh et al. (2003) and Venkatesh et al. (2012) in the context of the present study. Based on the constructs defined, performance expectancy is the HR professionals' belief that using HR analytics will be gainful towards their job. Effort expectancy is the HR professionals' belief about the ease of using HR analytics. Social influence is the HR professionals' perception of what the people (management, colleagues, peers, and other social groups) around them think about them using HR analytics. Facilitating conditions indicate the HR professionals' perception of the supportive conditions in the organization to use HR analytics. The widespread use of HR analytics clearly indicates the behaviour that HR professionals aim to take toward employing HR analytics. Secondary sources of information for the present study are considered from reputed databases and journals available with EBSCO, Emerald Insight, Taylor and Francis, J-gate, Springer, and Elsevier. The studies highlighting the importance of HR analytics and its adoption-related issues have been carefully considered for the purpose of the literature review. Considering the emerging nature of the area of HR analytics, reports on industry trends and HR professionals were examined by analyzing publications of professional organizations and consultancies such as CIPD, SHRM, Deloitte, and E&Y. This information helped in gaining an understanding of the progressive nature of the research topic and emerging evidence.

An overview of the study instrument is provided in Table 1. To rate the items under this construct, a five-point Likert scale is considered, as validated by Venkatesh et al. (2003). The scale with the anchor points, "strongly disagree", "disagree", "Neutral" "agree", and "strongly agree" (Brown, 2010; Vagias, 2006) was used.

Table 1

Constructs and Items Used in the Study Instrument

S. No.	Constructs	No. of Items	Item Description	Cronbach's alpha (Reliability)
1.	Performance Expectancy (PE)	4 items	PE1 "I would find HR analytics useful in my job." PE2 "Using HR analytics enables me to accomplish tasks more quickly." PE3 "Using HR analytics increases my productivity." PE4 "If I use HR analytics, I will increase my chances of getting a raise."	.88

2.	Effort Expectancy (EE)	4 items	EE1 "My interaction with HR analytics would be clear and understandable." EE2 "It would be easy for me to become skilful at using HR analytics." EE3 "I would find HR analytics easy to use." EE4 "Learning to operate HR analytics is easy for me."	.96
3.	Social Influence (SI)	4 items	SI1 "People who influence my behaviour think that I should use HR analytics." SI2 "People who are important to me think that I should use HR analytics." SI3 "The senior management of this business has been helpful in the use of HR analytics." SI4 "In general, the organisation has supported the use of HR analytics."	.88
4.	Facilitating Conditions (FC)	4 items	FC1 "I have the resources necessary to use HR analytics." FC2 "I have the knowledge necessary to use HR analytics." FC3 "HR analytics is compatible with other systems I use." FC4 "A specific person (or group) is available for assistance with HR analytics difficulties."	.82
5.	Adoption of HR analytics (AD)	5 items	AD1 "My organisation is putting a policy in place to use HR Analytics." AD2 "I am beginning to explore using HR Analytics." AD3 "I am interested in using HR Analytics." AD4 "I am recommending my organisation to invest in HR Analytics." AD5 "I use HR Analytics for some specific tasks."	.93

Results

The data collected in the present study has been analyzed, and the results are presented. The characteristics such as gender, age, and work experience of respondents are presented first.

Gender, Age, and Work Experience of Respondents

Table 2 presents the gender, age, and work experience of respondents. The data shows that the percentage of male respondents (71.8 percent) is higher than the percentage of female respondents (28.2 percent). Though, in general, the HR profession is believed to be occupied by more female members, the present study indicates that the presence of male members is still higher even in the HR profession. When respondents are grouped as per their ages, it is indicated that a significantly high representation of the respondents is from the 28-34 years age group. Respondents in the 28-34 age group are 41.3 percent of the total respondents. Of the total respondents, 32.6 percent are in the age group of 35-41 years. Nineteen percent of respondents are aged 21-27 years of the total respondents. While respondents in the 42-48 years age group are 4.9 percent, only 2.3 percent of respondents are aged above 49 years. The total work experience of the respondents indicates that (47.7 percent) close to half of the respondents, have total work experience less than or equal to five years. Of the total respondents, 40.3 percent represent the group with 6-12 years of work experience and 8.2 percent of respondents represent the group with 13-19 years. While 2.6 percent of respondents have 20-26 years of experience, only 1.3 percent of respondents have more than 27 years of experience.

Table 2

Demographic Characteristics of Respondents

Demographic Factor		No. of Respondents (n = 390)	
		Frequency	Percent
Gender	Male	280	71.8
	Female	110	28.2
Age (years)	21 - 27	74	19.0
	28 - 34	161	41.3
	35 - 41	127	32.6
	42 - 48	19	4.9
	49+	9	2.3
Total Work Experience (years)	<= 5	186	47.7
	6 - 12	157	40.3
	13 - 19	32	8.2
	20 - 26	10	2.6
	27+	5	1.3

A linear regression analysis was carried out. It was verified through linear regression whether the perceptual variables, including Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC)) significantly predicted Adoption (AD). Before going ahead with linear regression, normality, homoscedasticity, and outliers were assessed to satisfy the assumptions. The results indicated meeting all the required conditions.

Variance Inflation Factors (VIFs) were computed to verify multicollinearity between variables under study. VIFs above the value of five may increase multicollinearity. VIFs below 5 are acceptable (Menard, 2010). The data indicated that the VIFs of all variables in the regression model are less than 5. Table 3 presents the values of VIF computed for the variables in the model.

Table 3

Variance Inflation Factors

Variable	VIF
PE	1.47
EE	2.05
SI	1.90
FC	1.77

Table 4 shows the results of the linear regression of variables in the model. The linear regression model results were significant, $F(4,384) = 155.02$, $p < .001$, $R^2 = .62$. It can be inferred that 62% of the variance in the adoption of HR analytics (AD) among respondents is explainable by the perceptual variables under study according to the model tested under regression. Performance expectancy (PE) significantly predicted adoption (AD), $B = .31$, $t(384) = 8.05$, $p < .001$. Effort expectancy (EE) did not significantly predict adoption (AD), $B = .07$, $t(384) = 1.70$, $p = .09$. Social influence (SI) significantly predicted adoption (AD), $B = .27$, $t(384) = 6.71$, $p < .001$. Facilitating conditions (FC) significantly predicted adoption (AD), $B = .30$, $t(384) = 7.40$, $p < .001$.

From the results, it can be inferred that the adoption of HR analytics (AD) would see .31 units increase with each unit increase in performance expectancy (PE). The adoption of HR analytics would see a .27 units increase with each unit increase in social influence (SI). Also, the adoption of HR analytics (AD) would see .30 units increase with each unit increase in facilitating conditions.

Table 4

Results for Linear Regression with PE, EE, SI, and FC predicting AD

Variance	*B*	*SE*	95% CI	β	*t*	*p*
(Intercept)	.17	.14	[-.11, .45]	.00	1.17	.242
Performance Expectancy (PE)	.31	.04	[.24, .39]	.31	8.05	< .001
Effort Expectancy (EE)	.07	.04	[-.01, .16]	.08	1.70	.090
Social Influence (SI)	.27	.04	[.19, .35]	.29	6.71	< .001
Facilitating Conditions (FC)	.30	.04	[.22, .38]	.31	7.40	< .001

Note. Results: $F(4,384) = 155.02$, $p < .001$, $R^2 = 0.62$; Unstandardized Regression Equation: Adoption of HR analytics (AD) = 0.17 + 0.31*PE + 0.07*EE + 0.27*SI + 0.30*FC

Analysis of Differences in Adoption by Gender, Age, and Total Work Experience

The t-test (Two-tailed independent samples) is utilised in order to investigate the gender variations in the HR analytics adoption rates. An analysis of variance, often known as an ANOVA, was performed to determine whether or not there were significantly different rates of adoption based on age or total years spent in the workforce. Before moving on to the analysis of variance (ANOVA), the assumptions concerning the univariate normality of residuals, the homoscedasticity of residuals, and the absence of outliers were evaluated and validated.

The outcome of the t-test conducted on gender (Table 5) did not show any significant differences, $t(388) = .35$, $p = .72$, indicating that the mean of adoption was not significantly different between the male and female categories of gender.

Table 5

Two-Tailed Independent Samples t-Test for the Difference Between Adoption by Gender

	Male		Female				
Variable	*M*	*SD*	*M*	*SD*	*t*	*p*	*d*
Adoption	3.55	0.70	3.52	0.73	0.35	.729	0.04

Note. Degrees of Freedom for the *t*-statistic = 388. *d* represents Cohen's *d*.

The overall results of the ANOVA were significant, $F(6, 382) = 3.76$, $p = .001$, indicating there were significant differences in adoption (AD) among the levels of age and total work experience (Table 6). The results of ANOVA have shown that at the 95% confidence level, age was significant, $F(2, 382) = 5.92$, $p = .003$, $\eta_p^2 = .03$, which indicates that adoption levels among respondents were significantly different by age groups. It is also found that at the 95% confidence level, total work experience was significant, $F(3, 382) = 4.31$, $p = .005$, $\eta_p^2 = .03$, which indicates that adoption levels among respondents were significantly different by total work experience levels.

Table 6

Analysis of Variance Table for Adoption by Age and Total Work Experience

Term	*SS*	*df*	*F*	*p*	η_p^2
Age	3.35	2	5.92	.003	.03
Total Work Experience	3.66	3	4.31	.005	.03
Residuals	107.90	382			

Tukey post-hoc test was carried out for the total work experience. The results have shown that the mean of adoption for less than ten years experience of respondents ($M = 3.67$, $SD = .56$) was significantly larger than for 15-20 years of experience of respondents ($M = 3.49$, $SD = .40$), $p = .010$. Other than the total work experience, other effects were insignificant.

Summary of Results

Table 7 indicates the summary of results based on the hypothesis proposed in the study. Of the seven hypotheses proposed for the study, five are accepted. There is a significant relationship between performance expectancy, social influence, and facilitating conditions on the adoption of HR analytics among HR professionals. Effort expectancy has no significant relation to the adoption of HR analytics among HR professionals. Adoption levels were not significantly different among male and female HR professionals. Levels of adoption were significantly different among age groups and work experience.

Table 7

Summary of Results

Hypothesis	*P value*	Result
H_1: Adoption of HR analytics is significantly influenced by performance expectancy	< .001	Accepted
H_2: Adoption of HR analytics is significantly influenced by effort expectancy	.090	Rejected
H_3: Adoption of HR analytics is significantly influenced by social influence	< .001	Accepted
H_4: Adoption of HR analytics is significantly influenced by facilitating conditions	< .001	Accepted
H_5: There are differences in the adoption of HR analytics by gender	.729	Rejected
H_6: There are differences in the adoption of HR analytics by age	.003	Accepted
H_7: There are differences in the adoption of HR analytics by work experience	.005	Accepted

Discussion

Within the UTAUT model, there are a total of four perceptual variables. Three of these variables suggested that they have a substantial influence on the adoption of HR analytics. The adoption of HR analytics by HR professionals is not influenced by the expectation of the amount of work involved. The adoption of HR analytics was considerably influenced by the model's remaining three factors. This indicates that HR professionals' perceptions of how easy it is to use HR analytics could not have an effect on their intentions to use HR analytics. The usage of HR analytics is something that HR professionals are prepared to do, regardless of how simple or complex the process may be. As shown by performance expectancy, human resource management professionals who use HR analytics hope to achieve specific benefits or gains in the course of their work. It is possible that they will be less likely to utilise HR analytics if they do not see any benefit in utilising HR analytics to boost their work performance.

In a similar vein, the people that HR professionals interact with on a daily basis are crucial in improving the intention of HR professionals to use HR analytics. If colleagues, bosses, and other influential people in the organization want the HR professionals to be using HR analytics, HR professionals might consider adopting HR analytics. HR professionals with less than ten years of experience were more inclined to adopt than those with more than ten years of work experience. HR professionals who have recently been into the HR domain are adopting HR analytics more actively as they are more tech-savvy and flexible to adopt new technologies than those with more work experience.

While the present study did not find effort expectancy to be significantly influencing HR analytics adoption, the findings from the study by Ekka and Singh (2022) showed that all variables (PE, EE, SI, and FC) had a substantial favourable impact on behavioural intention to utilise HR Analytics. On the other hand, in the study in reference, the culture of the company was also found to be acting as a moderator that has a detrimental effect on the connection between HR Analytics adoption intention and adoption behaviour. In another study by Merkle and Steinman (2021), the results showed that HR practitioners' views on adopting new ideas are affected by how well they knew how to use data in their prior experience. HR professionals who understand business in areas other than HR are likely to use HR Analytics. The study results of Merkle and Steinman (2021) support the views of the present study wherein performance expectancy was found to be significantly influencing. Further, the study in reference states that in line with the idea of motivation, HR professionals who are excited about taking on new tasks and are not afraid to try new things are most likely to use HR analytics. Acceptance of new ideas is heavily affected by a wide range of personality traits and skills. A solution that is easy for its users to understand is also likely to make HR professionals more likely to use analytics. The present study has emphasized the need for facilitating conditions and the influence of the people around the HR professional, which can act as a significant motivator.

Implications

The present study leads to several implications at the managerial and theoretical levels. From the managerial implications, it is clear that as data and analytics have occupied the workplace, embracing HR analytics is inevitable sooner or later for organizations. To facilitate early adoption, organizations need to take the initiative. According to the findings of this study, in order for an organisation to maintain the readiness of its human resources professionals to adopt HR analytics, the organisation must first raise awareness of HR analytics and train its human resources professionals to recognise its utility in performing job-related functions. Visible outcomes with HR analytics will make HR professionals see the utility for their job and adopt HR analytics. Senior managers and immediate supervisors of HR professionals can play a significant role in influencing the adoption of HR analytics. Thus, senior managers and bosses of HR professionals need to continually motivate and encourage HR professionals to see the usefulness of HR analytics. HR analytics is a form of information technology that is sensitive to software and hardware requirements. Hence, organizations need to create the necessary infrastructure to enable HR professionals to adopt HR analytics. Young HR professionals and those in the growth phase of their careers should be encouraged to take up HR analytics-related tasks as readiness is observed among them. Similarly, measures should be taken to include other senior HR professionals to get trained and lead their juniors.

Limitations and Future Research

From a theoretical perspective, the present study implies including certain variables not considered in the study. As discussed by researchers, technology adoption models cannot be applied in the same manner over some time. With changes happening around the individuals and the emergence of new technological capabilities, the approach towards studying the adoption should also be modified. New models or improvised models from existing frameworks have to evolve. Besides testing the perceptions of users to adopt technologies, their preparedness and competence to adopt such technology should be assessed. Not just facilitating conditions but support from the management and active involvement of management can be studied as a separate dimension. Other factors such as trust, leadership, and supportive culture in the organization may be included in future studies and validated for theorizing the adoption.

Conclusion

The present research was carried out, keeping in view the theoretical propositions made by the UTAUT model. The results indicated validation of the model in establishing the relationship between the user’s perceptions and behavioral intentions while adopting a technology. The present study is limited in studying the various factors that may show the influence of adopting HR analytics. Differences in adoption levels are studied on gender, age, and work experience only. Future research may focus on studying the effects of other factors, such as education levels, training, and organizational support. The study covered several cities in India. However, all the organizations from different locations may not be reflected in the sample. Adoption levels may vary with the inclusion of other organization across the locations. The present study considered the views of HR professionals only. Views and opinions of other top managers may be studied further, which could influence adoption. HR professionals require analytical capabilities to flourish with HR analytics. How well the HR professionals are faring in terms of their analytical competencies can be an essential point for future studies. Whether the analytical competencies of HR professionals influence adoption levels can also be studied in the future.

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