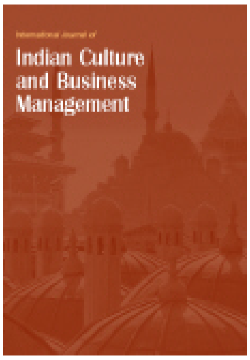

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Behavioural intention of HR professionals to use HR analytics in the Indian context: an analysis using the UTAUT model

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Abstract: Despite the need for innovation in HRM, HR professionals are still lagging in analytics, and various factors hinder the adoption of HR analytics. Its lower adoption rate is creating issues for developing countries such as India to achieve their full potential. This research aims to determine the factors impacting the behavioural intention in using HR analytics among the HR professionals from the perspective of the unified theory of acceptance and the use of technology (UTAUT) in the Indian context. A structured close-ended questionnaire is used to collect the data from different HR professionals in India. It is revealed that performance expectancy and effort expectancy significantly predict the behavioural intention of using HR analytics. However, social influence and facilitating conditions are not significant variables to influence behavioural intention and use behaviour, respectively, while behavioural intention is discovered as a direct factor of use behaviour.

Keywords: barriers; innovation; HR analytics; UTAUT model; behavioural intention.

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1 Introduction

The success of an organisation relies on the efficient utilisation of its employees. Organisations treat their employees as strategic assets to enhance their competitiveness and achieve strategic and competitive advantages. The HR-related data is a crucial element to make data-driven decisions. Hence, HR analytics has emerged as an opportunity for HR leaders in contributing to organisational strategy. HR-related data requires a proper and detailed analysis for enhanced decision making and better performance (Lochab et al., 2018). HR professionals are required to use HR analytics as an essential element in decision-making in organisations. The HR function has expanded over the years, but still, it is lagging behind and not generating desired outcomes. HR leaders' success is analysed not by creating the changes but through various qualities like employee attitudes, strength, turnover, etc. Organisations still lack the skills required to analyse their client's expectations and their effects on the performance (Boudreau and Ramstad, 2003). Lawler et al. (2004) revealed that HR analytics is an opportunity for the HR function to prove its value by considering the effects of HR plans and policies, predicting behaviour and developing relationships with various statistical tools.

HR leaders focus on exploring the past data and events and the outcomes generated from their recruitment processes, talent management, and the achieved goals (Harris et al., 2010). According to Mondore et al. (2011), HR analytics helps in various domains such as recruitment, selection, performance management, talent management, onboarding, etc., which leads to better return on investment. HR analytics extends from basic reporting of the HR data to predictive analytics, including forecasting, analysing the effects of policy changes, etc. (Bassi, 2011). Ejo-Orusa and Okwakpam (2018) found that HR practices and predictive HR analytics are significantly related to each other and suggested utilising predictive HR analytics in the HR processes to augment the performance of HR functions. Various organisations create dashboards for storing the HR data but don't use them to predict future tasks and measure outcomes (Harris et al., 2011). The analytical and statistical tools could provide analytical insights, forecast the trends and patterns, and make strategic decisions effectively at all organisation levels (Kapoor and Sherif, 2012). Fernandez (2019) posits that the adoption and usage of analytics in HR would increase the risk of unexpected discrimination, the requirement of analytical skills, and, most importantly, a centre of expertise dedicated to HR-related data and tools.

Pappas et al. (2018) highlighted that organisations understand the benefits and competitive gains of using and applying meaningful information. Shrivastava et al. (2018) highlighted the causes of interest in HR analytics: top-level managers' concentration towards computing decisions associated with the employees, the link between HR performance and analytics decisions, and the need for HR area be measurable and equally significant. Although HR analytics is gathering importance yet, the developing countries are lagging in adopting HR analytics (Vargas et al., 2018; Ejaz et al., 2020; Hettiarachchi et al., 2020; Alsuliman and Elrayah, 2021). Hettiarachchi et al. (2020) highlighted the relevance of environmental factors in the successful adoption of HR analytics. Alsuliman and Elrayah (2021) recommended using HR analytics to gain a competitive advantage and enhance organisational performance.

2 Research gap and objectives

The organisations have realised HR analytics potential and opportunities, but there remains a gap for its growth and adoption in the different HR functions. Although organisations view HR analytics as a high priority, its adoption is still significantly less, especially in developing countries. The low adoption rate of HR analytics creates issues for developing countries such as India to achieve their full potential. It is seen from the previous studies that the adoption of HR analytics is relatively slow in the HR department of organisations, mainly in developing countries (Marler and Boudreau, 2017; Vargas et al., 2018; Ejaz et al., 2020; Hettiarachchi et al., 2020; Alsuliman and Elrayah, 2021). Vargas et al. (2018) highlighted that the organisations' finance, operations, and marketing departments sophistically use predictive analytics for their daily operations while the HR departments are still exploring the basic metrics and analytics. Hence, there is a dire need for HR professionals to adopt and use analytics to keep pace with the other departments of the organisation and be strategic partners. Heuvel and Bondarouk (2017) pointed that organisations are still using descriptive analytics due to the scarce analytical skills of HR leaders.

The present research aims to fill the literature gap, i.e., the less adoption of HR analytics in the organisations (Marler and Boudreau, 2017; Vargas et al., 2018; Ejaz et al., 2020). This study aims to determine the factors that will promote or hinder HR analytics adoption in organisations. The study would also contribute to exploring the areas that need to be filled to adopt HR analytics. The study is viewed from the perspective of the unified theory of acceptance and the use of technology (UTAUT) model to figure out the slow adoption of HR analytics. This study considered the UTAUT model since it extends the practical ability limits for analysing user decisions for adopting technology since it describes approximately 70% of the intent difference. The present research examines the variables affecting the intent to adopt HR analytics among HR professionals in the organisation. The study identifies the relationship between different variables and how they influence HR professionals' behaviour to implement HR analytics.

3 Literature review

3.1 HR analytics

Workforce analytics is an approach using analytical tools to generate insights for building, managing and motivating the workforce to achieve better strategies (Hoffmann et al., 2012). Analytics provides meaningful and data-driven insights with the help of integrated and valuable data, appropriate competence, and proper statistical and analytical tools (Ranjan and Basak, 2013). Davenport et al. (2010) revealed that high-performance organisations have removed the guesswork and use HR analytics to align their business strategies and generate insights for various functions such as retaining talent and enhancing performance. Mohammed and Quddus (2019) stated that HR analytics is a rational approach that yields statistically relevant information for developing and implementing strategies, policies, etc., in the organisation. Organisations can utilise HR analytics in two different ways: regression analysis to find correlations and cause-effect analysis; for examining the various independent and dependent variables driving the effectiveness and ROI of an organisation (Mondore et al., 2011). HR analytics is helpful in different functions like identifying the training needs, predicting the demand and supply of the workforce, managing the rewards, benefits, employee discipline, etc. (Mohammed and Quddus, 2019). Watson (2013) categorised analytics into three types. Descriptive analytics involves analysing the past data and explains the relationship between them. It has dashboards, ad-hoc reports, SQL queries, and KPIs to interpret the historical data and identify the turnover rates, absence rates, etc. (Fitz-Enz, 2010). Predictive analytics makes use of statistics for predicting future trends and outcomes. Prescriptive analytics interprets the HR data using simulation and optimisation tools and yields data-driven decisions. Fitz-Enz and Mattox (2014) stated to develop an analytics value chain, models, and processes to convert the data into relevant information. It highlights various cases of successful predictive analytics generating insights for different issues.

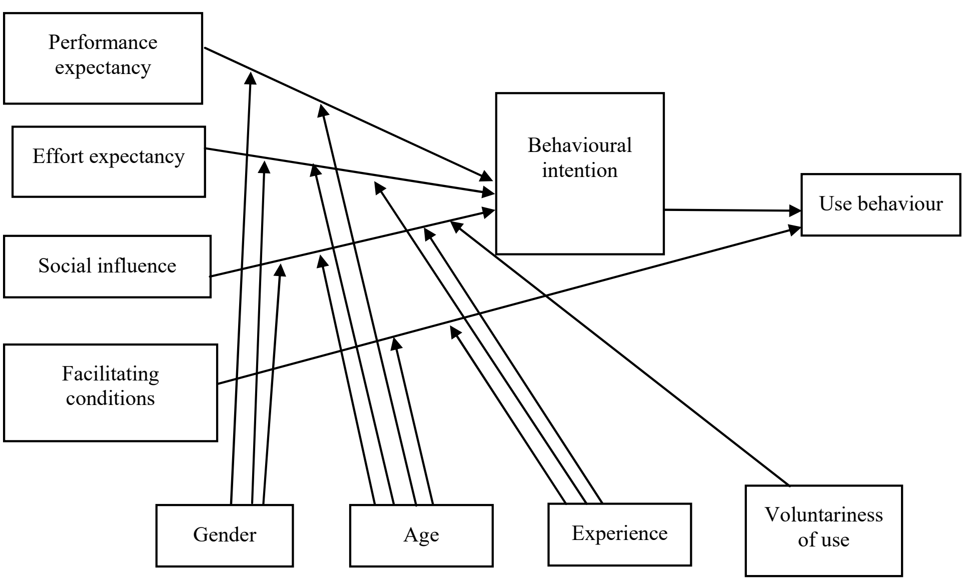
Huselid and Minbaeva (2019) highlight that HR analytics would bring a significant change in HR, and the HR professionals need to understand their roles to achieve success with the analytics adoption. Mondore et al. (2011) provided a way through the roadmap to involve HR analytics in the framing and aligning various organisational strategies and results. It recommends analysing the relevant outcomes, developing and executing plans, and altering them after the implementation to analyse the desired results. Levenson (2011) compared the impact analysis, cost-benefit analysis, and return on investment. It postulates the importance of metrics and analytics in generating analytical decision-making insights through various labour markets and organisational design models in different HR functions. The research advised utilising the organisational resources and capabilities by applying relevant analytics and driving the organisational outcomes. Mishra et al. (2016) stated that HR analytics is necessary for enhancing organisational performance, overall employee well-being, and advanced decision making in organisations. Patre (2016) studied the concept and importance of HR analytics and revealed that it could enhance the decisions, generate better insights for achieving maximum advantage and lead HR function to be a strategic partner. HR analytics can be utilised in various HR processes and functions; workforce compensation, workforce planning, recruitment and selection, talent retention, etc., for generating meaningful insights and making fact-based decisions (Uppal, 2020).

Similarly, Matheus et al. (2020) suggested using data-based panels in public sectors to generate insightful decisions and enhance the terms between the government and its public. Upadhyay and Khandelwal (2018) concluded that using Artificial Intelligence in the recruitment process helps control costs, increase profitability, and establish long-term relations with the candidates. DiClaudio (2019) recommended organisations develop analytical strategies and adopt advanced analytics to enhance the hiring process, thereby achieving strategic and competitive advantages.

Ranjan and Basak (2013) pointed out various Pull-factors that HR analytics require, such as efficient utilisation of resources, suitable talent, data-driven decisions, and less traditional methods. Various push-factors determined are automated information, scientific advancement, etc. A study determined different dimensions of HR analytics (such as descriptive, diagnostic, predictive, and prescriptive analytics) and assessed the relationship between HR analytics and job engagement. It is found that the dimensions of HR analytics promote employee engagement when utilised efficiently, mainly in the manufacturing sector (Oladipupo and Olubusayo, 2020). Organisational and cultural factors, specifically insufficient skills and capabilities, lack of tools and technologies, are identified as the main barriers hindering analytics in organisations (Vidgen et al., 2017; Vargas et al., 2018). Factors such as lack of relevant data, political issues, top management support, technical expertise are revealed as factors responsible for the slow adoption of HR analytics (Keerthi and Reddy, 2018). Beka and Behrami (2019) conducted a study to identify the barriers Swedish organisations face for adopting HR analytics and found that factors such as metrics, trust and competence in technology act as barriers during the adoption of HR analytics.

In a study, Atchyutun and Kumar (2019) developed a model to analyse and differentiate factors impacting HR analytics adoption as driving, autonomous, linking, and dependent factors. Factors such as data reliability, IT collaboration, vendor assurance, in-house experts, and technical ease are indicated as driving factors. Leaders view HR analytics, data security, HR attitude, and outlook; return on investment assurance is categorised as dependent factors. A data-driven culture is found to be a linking factor that affects all other adoption factors. Luo et al. (2018) stated that complicated models used in HR analytics provide obscure and complex outcomes that require proper analytical software to use analytics and understand its results. Tomar and Gaur (2020) highlighted legal and ethical issues in using the data, quality of data, lack of analytical skills, and top management support as few challenges in adopting HR analytics. It is stated that these challenges can be overcome with the benefits provided by the use of HR analytics, such as competitiveness, enhanced HR functions, and organisational performance. The adoption of HR analytics is considerably slow because of various privacy concerns, capability gaps, etc.

Figure 1 UTAUT model



Source: Venkatesh et al. (2003)

3.2 The unified theory of acceptance and the use of technology

Technological Innovations has brought different models with several determinants. Venkatesh et al. (2003) formulated the UTAUT model by examining eight adoption theories. Its significant determinants are performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). It includes moderators such as age, experience, the voluntariness of use, and gender. This model depicts a direct relation of PE, EE, SI on the users' BI and determinant; FC is directly related to the user behaviour. It reveals the technology acceptance drivers and the benefits of contextual analysis to frame strategies for implementing technologies.

3.3 Prior research and theoretical background

There are various studies on innovation adoption, but few studies are on adopting/rejecting innovation at the individual level. Jeyaraj and Sabherwal (2008) stated that embracing innovation is a varied process involving individuals affected by other individuals' behaviour. Various studies have applied the UTAUT model to analyse technology adoption (Im et al., 2011). These include Internet banking adoption (AbuShanab and Pearson, 2007), understanding students perception regarding the management software (Marchewka and Kostiwa, 2007), identifying the determinants of web-based services adoption (Deng et al., 2011), analysing students' ICT adoption (Attuquayefio and Addo, 2014), and determining human resource information systems (HRIS) adoption factors (Rahman et al., 2016). According to Buzkan (2016), HRIS is an information system that helps in gathering, storing, and analysing the HR data related to employees pay, employees' benefits, appraisals, etc., in an organisation.

A study conducted from the perspective of UTAUT without considering the moderators affirmed that variables PE, EE are positively related to BI. In contrast, SI and FC do not influence BI and UB, respectively (Carlsson et al., 2006). Lesser and Hoffman (2012) revealed that top-level management considers HR an essential opportunity to achieve competitive advantage and efficient performance with the adoption and use of analytics. Top-level believes the adoption of HR analytics is necessary at the individual level to achieve its intended benefits.

In a study, the UTAUT model is relevant in predicting the factors related to technology usage and adoption. It indicated that EE and SI positively impact technology adoption, whereas support and time hinder the technology adoption (Oye et al., 2014).

Although various researches have highlighted that organisations are using HR analytical tools and software, there is still insufficient proof of advanced HR analytics (Davenport, 2019). A study conducted by Vargas (2015) analysed variables affecting the individual level adoption of HR analytics. It showed that factors such as SI, PE, quantitative self-efficacy, tool availability, and EE significantly impact HR analytics adoption. While, factors such as general self-efficacy, data availability, and fear appeals negatively affect the adoption of HR analytics. Also, data availability does not drive the HR analytics adoption, and limited or no resources would hinder the HR analytics adoption at the individual level. The knowledge of technology and the analytics culture are the top barriers to adopting analytics (Halper, 2014). Vargas et al. (2018) used the Diffusion of Innovation Theory, identified factors promoting or hindering the adoption of HR analytics and suggested ways to boost the analytics adoption.

Fobang et al. (2019) conducted a study to determine the factors influencing the Human Resource Information system adoption in the Cameroon context using the UTAUT model. It revealed that elements such as PE and SI significantly affect the adoption of HRIS, and FC does not influence the use of HRIS. The adoption intention directly affects the use of HRIS. Young age respondents significantly affect the adoption, while respondents with a low education background need the adoption of HRIS. Pongpisutsopa et al. (2020) conducted a study using the UTAUT model, technology-organisation-environment framework, and diffusion of innovation theory. They revealed top factors, data availability, top management support, and quantitative self-efficacy that influence the adoption of HR analytics. Hettiarachchi et al. (2020) analysed the influence of environmental factors (data availability, fear appeals, tool availability, and SI) on adopting HR analytics at an organisational level. The findings indicated that all the above environmental factors significantly affect the adoption of HR analytics and thus, should be considered. Alsuliman and Elrayah (2021) studied the UTAUT factors; PE, EE, tool availability, SI, data availability, and self-efficacy to analyse the less adoption of HR analytics amongst HR professionals. All the above factors are positively related to HR analytics adoption, with EE being the top influencing factor in the adoption decision of HR analytics, followed by self-efficacy and data availability. Qureshi (2020) analysed whether HR analytics is a fad or just a fashion and found out that HR analytics produces considerable outcomes in organisational sustainability and urged organisations to provide analytical training to the employees and adopt HR analytics.

4 Hypotheses development and proposed model

Performance expectancy

PE is an employee's belief that a particular system/technology would provide them performance gains (Venkatesh et al., 2003). PE is drawn from five variables, i.e., job-fit, perceived usefulness, relative advantage, extrinsic motivation and outcome expectations. Venkatesh et al. found PE as significant and consistent with the past models, and it strongly predicts the users' intention. The age and gender of users moderates PE and users' intention. It is argued that men tend to be more task-oriented, and PE determines the intention more significantly for men and young users.

H1 PE directly influences the HR professionals behavioural intention (BI) to adopt HR analytics.

Effort expectancy

EE can be said to ease or comfort using the particular technology (Venkatesh et al., 2003). This construct is obtained from three constructs; complexity, perceived ease of use, and ease of use. EE is significant during the first period and insignificant with the extended use (Venkatesh et al., 2003). Gender and age moderate the EE, which significantly affects women and older users, which reduces the experience.

H2 EE directly influences the HR professionals BI to adopt HR analytics.

Social influence

SI is the impact of others persuasion on the individual towards using new technology. This construct directly determined the BI and revealed it insignificant when data were analysed without including the moderators. Some studies of technology adoption, such as Thompson et al. (1991), Taylor and Todd (1995), have formed the construct, SI, while Davis (1989) have not taken it into their study (Venkatesh et al., 2003). Venkatesh and Davis (2000) revealed that SI significantly influences technology adoption only in mandatory settings.

H3 SI directly influences the HR professionals BI to adopt HR analytics.

Facilitating conditions

FC measure a person's belief towards the availability of necessary support and resources (Venkatesh et al., 2003). This construct is derived from three constructs; FC, perceived behavioural control, and compatibility. It is found that FC affects the user behaviour and is significant only when data is analysed with the moderators; age and experience.

H4 FC directly influence the Use behaviour of HR analytics.

Behavioural intention

Behavioural intention measures an individual's intention in using HR analytics (Venkatesh et al., 2003). Various researches identified a positive relationship between BI and use behaviour (UB) (Fishbein and Ajzen, 1977; Venkatesh et al., 2003; Weerakkody et al., 2013).

H5 Behavioural Intention directly influences the Use behaviour of HR analytics.

Use behaviour

It involves an individual's acts, both mental and physical, to integrate the information derived from the existing database (Wilson, 2000).

Moderating variables

Variables such as age, experience, gender, and voluntariness of use were used to analyse their moderating effect on the different constructs (Venkatesh et al., 2003). Previous research has analysed these moderating variables to determine the BI to use new technologies (Venkatesh et al., 2003; Birch, 2009; Tibenderana et al., 2010). The study determines the moderating effect of three variables, i.e., age, gender, and experience, and discarded the voluntariness of use. The study is not organisational based, and individual behaviour is optional and voluntary. Following hypotheses are used for determining the moderating effect:

H6a Age significantly moderates the relationship between constructs (PE, EE, SI) and BI.

H6b Gender significantly moderates the relationship between constructs (PE, EE, SI) and BI.

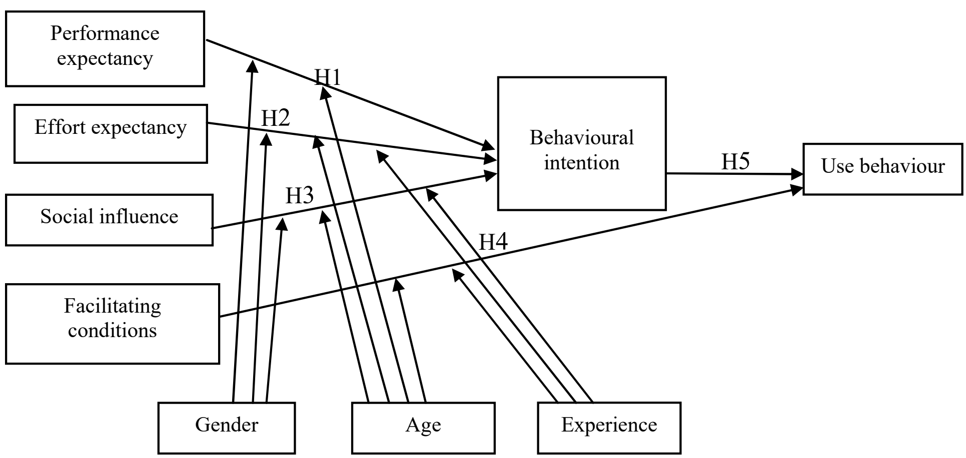
H6c Experience significantly moderates the relationship between constructs (EE, SI) and BI.

H6d Age and experience moderate the relationship between the independent variable, FC and the dependent variable, UB.

4.1 Proposed model

The model below is taken for this study as the conceptual model.

Figure 2 Proposed model



Source: Venkatesh et al. (2003)

5 Research methodology

The present study is viewed through the determinants of the UTAUT model, including four independent variables; PE, EE, SI, and FC, two dependent variables; BI and UB. The technology acceptance model and UTAUT model depicted the construct, user intention as the significant factor, and Venkatesh et al. (2003) described that it strongly predicts technology's actual use. The study aims to determine the value of factors (PE, EE, SI and FC) affecting HR professionals' usage intention and adopt HR analytics in the Indian context.

5.1 Measurement development

A close-ended questionnaire was used for collecting the data, with the first part including necessary demographic information. Another part contains variables related questions based on a five-point Likert scale, ranging from 1 to 5, with 1 as strongly disagree, and 5 as strongly agree. The four independent variables taken are PE, EE, SI, and FC. The two dependent variables include BI and UB.

Measurement items of the questionnaire

Table 1 Measurement items

S. no.	*Constructs*	*Adapted from*		*Measurement items*
1	Performance expectancy	Venkatesh et al. (2003)	PE1	I would find HR analytics useful in my work.
			PE2	Using HR analytics enables me to accomplish my tasks more quickly.
			PE3	Using HR analytics increases my productivity.
			PE4	Using HR analytics will increase my chances of getting a raise.
2	Effort expectancy	Venkatesh et al. (2003)	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.
3	Social influence	Venkatesh et al. (2003)	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 organisation is very helpful in the use of HR analytics.
			SI4	In general, the organisation supports the use of HR analytics.
4	Facilitating conditions	Venkatesh et al. (2003)	FC1	I have the resources necessary to use HR analytics.
			FC2	I have the knowledge necessary to use HR analytics.
			FC3	. HR analytics is not compatible with other systems I use in the organisation.
			FC4	A specific person (or group) is available to help if I have difficulty using HR analytics.
5	Behavioural intention	Venkatesh et al. (2003)	BI1	I intend to use HR analytics in the next few months.
			BI2	I predict I would use HR analytics in the next few months.
			BI3	I plan to use HR analytics in the next few months.
6	Use behaviour	Venkatesh et al. (2003)	UB1	I often use HR analytics to manage my task.
			UB2	I am satisfied with my decision to use HR analytics.

5.2 Survey administration

Primary data is gathered through the close-ended questionnaires filled by the HR employees working in the HR department of IT organisations. IT organisations were chosen since they contributed the highest proportion (19%) to the total revenue share in India (AIM, 2020). Secondary data was gathered extensively from the research papers, books, etc., published on technology adoption, HRIS, analytics, HR analytics, etc.

5.3 Data collection

The questionnaire was sent to the target population online through personal e-mails and accounts. Online surveys are considered an effective means for studying the users' behaviour relating to information technology (Park et al., 2007). The questionnaire was sent to 275 employees working in the HR department of IT organisations in India, and the response rate was 50%.

5.4 Data analysis

SPSS tool version 20 was used to analyse the collected data. Descriptive statistics, Frequencies, and Percentage were performed at a significance level of 5%. It helps in explaining the variables and inducing the information from the targeted sample. Pearson Correlation test (test to examine the relation between two numeric variables) was used to analyse and measure the relationship between the constructs taken in this study (Fisher and Buglear, 2010). Multiple linear regressions would examine different independent factors affecting HR analytics adoption amongst the HR department employees and analyse the proposed hypotheses.

5.5 Data analysis tools and techniques

SPSS is used for analysing the data, including descriptive statistics, correlation, and Cronbach alpha. Cronbach alpha determined the Internal consistency, taking alpha value < 0.70. Pearson Correlation was conducted to determine the convergent and discriminant validity of the model constructs. Saunders et al. (2009) suggested a regression analysis to determine the relationship strength between independent variables and a dependent variable.

Multiple regression analysis was administered to examine the factors that affect the BI of users' to adopt HR analytics in organisations.

5.6 Data analysis and presentation

Demographics and descriptive statistics

Regarding the respondents' position in the organisations, 68.6% worked at the middle level, 22.9% at the top level and 8.6% were lower. Concerning gender, 48.6% of the respondents were females, and 51.4% were males, a fair distribution. A large part of respondents, i.e., 48.6% were 26–30 years, 22.9% were among the 20–25 years category, 17.1% were in 31–35 years, 8.6% were among 36–40 years, 2.9% were among 40 and above. In addition, 91.4% had a masters' degree, while 8.6% had a bachelors' degree. 8.6% of the respondents had an experience of less than one year, 51.4% had an experience of 1–5 years, 31.4% respondents were having experience of 6–10 years, 5.7% had experience of 11–15 years, and 2.9% of the respondents had an experience of 16–20 years.

However, analysing respondents' experience in using HR analytics, most respondents (48.6%) have moderate experience, 11.4% have no experience. In comparison, 20% have low experience, and 20% are highly experienced using it. Descriptive statistics were performed to analyse if any item of the constructs is missing or not. It is found that no item is missing in the data.

Reliability and validity analysis of the instrument

Reliability analysis indicated that Cronbach alpha of PE = 0.795, EE = 0.873, SI = 0.541, FC = 0.731, BI = 0.875 and UB = 0.719. The Cronbach alpha for all the constructs is higher than 0.70, except SI. It is seen that Cronbach alpha of SI would be 0.713 if the first question is deleted. The first item related to SI is removed to get an acceptable range of Cronbach alpha. Cronbach alpha moved to 0.713, indicating a high degree of the coefficient. Table 2 shows that the reliability of constructs agrees with the psychometric reliability minimal scores, which is greater than 0.70 (Nachmias and Nachmias, 2008).

Table 2 Reliability analysis

Model constructs	*Cronbach alpha coefficient*
Performance expectancy	0.795
Effort expectancy	0.873
Social influence	0.713
Facilitating conditions	0.731
Behavioural intention	0.875
Use behaviour	0.719

Table 3 Correlation coefficient

	PE	*EE*	*SI*	*FC*	*BI*	*UB*
PE						
EE	.753**					
SI	.563**	.474**				
FC	.555**	.613**	.456**			
BI	.449**	.384*	.132	–0.70		
UB	.584**	.627**	.566**	.245	.628**	

Notes: **Correlation is significant at the 0.01 level (two-tailed).
*Correlation is significant at the 0.05 level (two -tailed).

Reliability is considered excellent when points are 0.90 and more than 0.90, high between 0.70–0.90, high- moderate between 0.50–0.70, and low when 0.50 and less than 0.50 (Nachmias and Nachmias, 2008). As shown in Table 2, reliability ranged between 0.713 to 0.875, representing the high and acceptable reliability of the model constructs. Table 3 depicts the Pearson correlation coefficient of all the dependent and independent variables. All the items were loaded on the respective constructs significantly (p-value more than 0.01). Each item was significantly loaded on its respective constructs; p-value greater than 0.01. The correlation of all the factors is more significant than 0.50. Hair et al. (1998) suggested that the factor loadings' acceptable validity is more than 0.50; hence, all the model constructs in the present study have a strong reliability measurement and establish the instrument's validity.

Pearson correlation

The correlation coefficient (range value between –1.00 and +1.00) determines the statistical link between two or more variables. A positive value indicates a direct link between variables; a negative coefficient indicates an indirect relation, and value 0 shows no correlation (Sedgwick, 2012). Pearson correlation test analyses the strength of the linear relationship between PE, EE, SI with BI, FC with UB, and BI with UB. It draws a line of fit through two variables in the dataset (Saunders et al., 2009). Pearson correlation coefficient results indicated a direct and strong relation between PE and BI, $r = 0.449$, $p < .01$, followed by BI and UB ($r = 0.628$, $p < .001$). A positive correlation is found between EE and BI ($r = 0.384$, $p < .05$); SI and BI ($r = 0.132$, $p > .05$); and lastly, FC and UB ($r = 0.245$, $p > .05$).

The ANOVA results (predictors, SI, EE, PE with dependent variable as BI) show a significant value of 0.041 ($p < 0.05$), revealing a substantial result. F-value is 3.106 (greater than 1), which means that the model is fair and efficient. Taking UB as a dependent variable and predictors as BI, FC, ANOVA represented a significant value (p-value) of 0.000 ($p < 0.001$), which indicates that the result is substantial. F-value is 14.699 (greater than 1), which shows a fair and efficient model.

Model and hypotheses testing

Multiple linear regression determines the relationship between various constructs. The hypotheses were tested using multiple regression analysis to know if the variables (PE, EE, SI and FC) impact the users' Behavioural Intention and UB as a dependent variable. Regression analysis predicts one dependent variable from the various independent variables (Saunders et al., 2009). Multiple regression analysis determined the research hypotheses and identify if independent variables (PE, EE, SI, FC) affect the BI of users of HR analytics.

Multiple linear regression analysis

Hypotheses testing were done with multiple regression analysis using SPSS. The regression analysis analysed the effect of independent variables such as PE, EE and SI on the users' BI. Regression analysis was conducted to investigate the impact of PE, EE and SI on the users' BI and the impact of FC and BI on UB. Table 4 and Table 5 represent the regression results. In Table 4, Adjusted $R^2 = 0.157$ indicates that the independent variables reveal 15.7% of the variance in the dependent variable.

Table 4 Regression of PE, EE, and SI on BI

	β		*t-value*	*Sig.*	*F-value*
PE	0.449		2.889	0.007*	3.106
EE	0.388		2.422	0.021*	
SI	0.132		0.766	0.449	
R		0.481			
R^2		0.231			
Adjusted R^2	0.157				

Notes: *$p \leq .05$
PE = performance expectancy; EE = effort expectancy; SI = social influence.
Dependent variable: behavioural intention (BI).

Table 5 Regression of FC, BI on user behaviour

	β		*t-value*	*Sig.*	*F-value*
FC	0.291		2.272	0.000**	14.699
BI	0.649		0.156		
R		0.692	5.071		
R^2		0.479			
Adjusted R^2		0.446			

Notes: $^{**}p \leq .001$
FC = facilitating conditions; BI = behaviour intention.
Dependent variable: use behaviour (UB)

The value of R is 0.481 (greater than 0.4), which indicates a good correlation between the independent variables (PE, EE, SI) and the dependent variable (BI). Table 5 reveals that adjusted R^2 = 0.446, indicating that independent variables (FC, BI) define 44.6% of the variance in the dependent variable (UB). Also, R-value, 0.692, represents a good correlation between independent variables (FC, BI) and dependent variable (UB). Table 6 below depicts the regression coefficients, including the moderating variables.

Table 6 Regression coefficient with moderating variables

Model	*Unstandardised coefficients*		*Standardised coefficients*	*t*	*Sig.*
	B	*Std. error*	*Beta*		
PE × gender	–.004	.347	–.015	–.012	.041*
EE × gender	.060	.308	.198	.194	.004**
SI × gender	–.537	.437	–1.658	–1.229	.028*
PE × age	.036	.166	.306	.219	.036*
EE × age	–.073	.171	–.548	–.424	.000***
SI × age	–.132	.218	–.920	–.607	.548
FC × age	.080	.258	.423	.312	.757
EE × exp	–.410	.208	–2.529	–1.966	.638
SI × exp	.052	.292	.302	.177	.000***
FC × exp	–.014	.341	–.064	–.041	.967

Notes: R^2 = 52.6%
$^{**}p \leq .01$ $^{*}p \leq .05$ $^{***}p \leq .001$.

5.7 Research constructs

Performance expectancy

Table 4 shows that construct PE with path coefficient value = 0.449 ($p < 0.05$) positively impacts the Behavioural Intention to use HR analytics. It supports the first hypotheses developed in this study, and results agree with the researches of Al-Khatib et al. (2019), Arif et al. (2018), Alshehri et al. (2012), Dey and Saha (2020), Hoque and Sorwar (2017), Khechine et al. (2014) and Venkatesh et al. (2003). Also, PE strongly predicts BI to use HR analytics amongst other constructs agreeing with the results of Khechine et al. (2013, 2014), and Venkatesh et al. (2003).

Effort expectancy

Table 4 revealed that EE with path coefficient value = 0.388 ($p < 0.05$) positively influences the BI to use HR analytics. The results support the second hypothesis developed in this study and agree with the studies of Al-Khatib et al. (2019), Alshehri et al. (2012), Arif et al. (2018), Hoque and Sorwar (2017), Dey and Saha (2020) and Venkatesh et al. (2003).

Social influence

The results in Table 4 revealed that SI does not positively influence the BI to use HR analytics with the path coefficient value = 0.132 ($p > 0.05$). Thus, the third hypothesis is rejected, and the results are consistent with the studies of Alshehri et al. (2012), Al-Khatib et al. (2019), Weerakkody et al. (2013).

Facilitating conditions

The results in Table 5 found that FC does not positively impact UB with the path coefficient value = 0.291 ($p > 0.05$). Thus, the results reject the fourth hypothesis, and the findings agree with the results of Carlsson et al. (2006), Hoque and Sorwar (2017), Dey and Saha (2020).

Behavioural intention

Table 5 depicted that BI directly determines UB with the path coefficient = 0.649 ($p < 0.001$). Thus, the results support the fifth hypothesis and are consistent with the results of Hoque and Sorwar (2017), Weerakkody et al. (2013), Dey and Saha (2020). Table 7 represents the summary of the hypotheses proposed in this study.

Table 7 Summary of the results of hypotheses testing

Hypothesis	*Path*	*Moderators*	*p-value*	*Result*
H1	PE → BI	-	0.007	Accepted ($p < 0.05$)
H2	EE → BI	-	0.021	Accepted ($p < 0.05$)
H3	SI → BI	-	0.449	Rejected ($p > 0.05$)
H4	FC → UB	-	0.156	Rejected ($p > 0.05$)
H5	BI → UB	-	0.000	Accepted ($p < 0.001$)
H6a	PE → BI	Age	0.036	Accepted ($p < 0.05$)
	EE → BI		0.000	Accepted ($p < 0.001$)
	SI → BI		0.548	Rejected ($p > 0.05$)
H6b	PE → BI	Gender	0.041	Accepted ($p < 0.05$)
	EE → BI		0.004	Accepted ($p < 0.01$)
	SI → BI		0.028	Accepted ($p < 0.05$)
H6c	EE → BI	Experience	0.638	Rejected ($p > 0.05$)
	SI → BI		0.000	Accepted ($p < 0.001$)
H6d	FC → UB	Age	0.757	Rejected ($p > 0.05$)
	FC → UB	Experience	0.967	Rejected ($p > 0.05$)

Interaction effects of moderators

The moderation effect is determined by multiplying the moderator and independent variable. The regression analysis involves the moderating variables, independent variables, dependent variables, and the multiplication of moderating variables with the independent variables. This study analyses the moderating effect of age on PE, EE, SI, FC towards BI, gender on PE, EE, SI towards BI, and experience on EE, SI towards BI.

The effect of gender, age, and experience

Table 7 presents the regression coefficients, representing gender as a significant moderator between PE, EE, SI and BI to use HR analytics, agreeing with the studies of AbuShanab and Pearson (2007), Kropf (2018) and Venkatesh et al. (2003). It is found that age significantly moderates PE, EE and BI to use HR analytics, consistent with AbuShanab and Pearson (2007), Kropf (2018) and Venkatesh et al. (2003). However, age is not found to be a moderator between SI and BI, FC and UB to use HR analytics. In the case of experience, the regression analysis indicated that experience strongly moderates the relation between SI and BI. Simultaneously, no moderation effect exists between EE and BI and FC and UB to use HR analytics in the organisations. The results are consistent with the studies of AbuShanab and Pearson (2007) and Kropf (2018).

6 Discussion and findings

The study determines the BI to use HR analytics by using the UTAUT model. The present research supports the UTAUT model, including three direct determinants of BI, i.e., PE, EE, and SI. The construct, UB, is determined by two factors; FC and BI. The present study reveals that PE and EE are directly related to BI for using HR analytics. However, FC is not positively related to UB, while BI is positively associated with UB. The findings reveal that HR professionals are more likely to adopt and use HR analytics if HR analytics is useful, reduces work time, and increases productivity and salary. Also, the easy use, clear interaction and simple learning process of HR analytics would positively influence the HR professionals to adopt it. However, societal influence doesn’t impact the users’ adoption and use of HR analytics. Top management and organisation support is not considered significant in driving the intention to adopt HR analytics. FC such as required resources, knowledge, support, and compatibility of HR analytics with other technologies are not considered significant in influencing the Use Behaviour. The study found that BI is significantly linked to UB, i.e., BI positively influences use behaviour.

The study revealed that PE, EE are relevant factors of the BI to use HR analytics, agreeing with Al-Khatib et al. (2019), Arif et al. (2018), Alshehri et al. (2012), Dey and Saha (2020), Hoque and Sorwar (2017) and Venkatesh et al. (2003). SI was discovered as a non-significant factor in HR analytics, which generally contradicts the result of the UTAUT model. The results related to the factor, SI, agree with the results of Alshehri et al. (2012), Al-Khatib et al. (2019), Weerakkody et al. (2013). The present research found that FC does not significantly influence UB to adopt HR analytics, consistent with the results of Carlsson et al. (2006), Hoque and Sorwar (2017), Dey and Saha (2020). However, the results are inconsistent with the previous studies, which support a positive relation between FC and UB in technology adoption. The moderating effect of variables, i.e., age, gender, and experience, determined that age is a significant moderator between PE, EE and BI. Simultaneously, it does not moderate SI and BI, and FC and UB to use HR analytics. Gender is a significant moderator between PE, EE, and SI and BI to use and adopt HR analytics. The moderator experience significantly moderates the relationship between SI and BI. At the same time, it does not affect the relationship between EE and BI and FC and UB to use HR analytics in the organisations. The results of moderating variables agree with AbuShanab and Pearson's (2007) and Kropf (2018) results. The results of studies such as Davenport (2006), LaValle et al. (2011) recommended boosting change agents, developing trust among the HR leaders, and creating an analytics culture. Huselid and Minbaeva (2019) highlight that HR analytics would bring a significant change in HR, and the HR professionals need to understand their roles to achieve success with the analytics adoption.

7 Contributions to the knowledge

The study is significant and contributes to HRM as it determines the users' behaviour towards adopting HR analytics in a developing country. The concept of HR analytics is still new in developing countries, and HR professionals are exploring the unfilled areas related to big data, metrics, and analytics. According to the literature reviewed, this is a preliminary study determining the variables influencing employees' behaviour towards adopting HR analytics in India. The present research enhances our expertise in HR analytics by analysing different factors impacting HR analytics adoption, taking the constructs of the UTAUT model. The study validates the importance of the proposed model of UTAUT and depicts the relationship between different constructs in the Indian context. It is revealed that various productive organisations have started executing analytics 3.0 (Davenport, 2013; Molefe, 2013), whereas there are still vacant areas that are required to be explored in the field of analytics, mainly in the developing countries (Boudreau and Ramstad, 2003; Marler and Boudreau, 2017; Vargas et al., 2018; Ejaz et al., 2020). The study provides theoretical, methodological, and practical implications.

8 Implications

8.1 Theoretical implications

The study aimed to identify the factors promoting or hindering the adoption of HR analytics in the IT sector across India. The study advances the academic literature in HR analytics and its adoption. Moreover, PE strongly determines the BI to use HR analytics, while SI has no impact on the users' intention. Consistent with numerous studies, BI is found to directly affect technology use, while, FC were revealed as a non-significant factor. The findings support some of the studies and also contradict some other studies.

8.2 Methodological implications

Using the UTAUT model to adopt HR analytics provides insights and scope to future researchers to utilise the model as a methodological contribution. The study used the

UTAUT model in the Indian context, which explains 70% of the variance in Behavioural Intention. It provides an approach explaining individual behaviour towards using and adopting HR analytics in organisations in developing countries.

8.3 Practical implications

The present study provides an approach to HR leaders to examine the significant and non-significant factors for achieving maximum output. The insights resulting from this study help determine employees' perceptions and behaviour towards adopting HR analytics. The study would help the HR professionals both within India and also in other developing countries. It provides excellent potential for HR analytics in organisations and highlights factors influencing the adoption of HR analytics. These factors guide HR leaders to focus on the adoption barriers and how to overcome these barriers potentially. The study gives valuable data about the reliability and validity of HR analytics in the developing world.

According to this study, HR professionals should focus more on employees' performance expectations and positively impact employees' behaviour. However, HR leaders can give less attention to SI and FC. The study found that SI is not directly related to BI, FC and user behaviour. Moreover, the decision-makers should be aware that BI directly affects user behaviour. So, a positive intention to use HR analytics would positively affect user behaviour.

9 Limitations and future directions

The present study is conducted by considering convenience sampling, which cannot represent the entire population. Although the UTAUT model is a significant, mature, and well-tested model, more relevant variables might affect HR analytics adoption in organisations. More research is required on HR analytics since this study highlights a few factors influencing HR analytics adoption. In addition, there may be various other factors impacting the BI to use HR analytics in developing and developed countries.

Moreover, the present study can be repeated in a different context generalising the results to other organisations and providing different results in a mandatory setting.

The research includes data from the HR professionals of the IT sector in India, which could not be generalised to all the other sectors in India and other countries. Hence, the future study can include other sectors such as the Banking and Financial sector, Manufacturing Sector, etc., in their research. Future research can be conducted by adding more constructs to the UTAUT model, such as risk involved, culture, privacy concerns, etc.

Conflict of interest

The author confirms that all funding sources that supported the work and all institutions and people who contributed to the job but did not meet the authors' criteria are acknowledged. The author also confirms that all commercial affiliation, stock ownership, equity interests, or patent-licensing arrangements that could be considered to pose a financial conflict of interest in connection with the article have been disclosed.

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