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Factors Affecting Adoption of HR analytics: A Study of IT Industry.

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How to cite this article:

Raj R *et al.* Factors Affecting Adoption of HR analytics: A Study of IT Industry. J Int Commer Law Technol. 2025;6(1):1346–1355.

Received: 04-09-2025

Revised: 24-10-2025

Accepted: 03-11-2025

Published: 11-11-2025

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Abstract: **Background:** Innovation in HR has led organizations worldwide to adopt Human Resource Analytics (HRA) among HR professionals. The advancement of technology in HR has induced the application of HRA for organizational decision-making in an effort to scale up HR analytical adoption. Adoption of HRA is highly influenced by several factors like personal and organizational factors to use HR analytics, but which factor influences mostly in the IT industry is a matter of investigation. With the development and advancement of tools, techniques, and technology, it is important to focus on particular factors that help better adopt HR analytics. **Purpose:** This study aims to investigate the adoption of HR analytics in Indian ITES and IT companies. The main goal of the article is to determine the elements influencing an individual level of employees with regard to the adoption of human resource analytics. **Methodology:** This proposed study will be exploratory in nature. Primary data collection will be through a structured questionnaire, with the targeted respondents being employees of Concentrix and Wipro. To determine the elements that have the greatest influence on HR analytics, exploratory factor analysis (EFA) will be used. Both snowball sampling and convenience sampling will be used to gather the data. **Scope:** The highlighted elements can assist the industry in changing its strategic direction for the better. The foundations for future study in human resource analytics will be laid out in this paper. This paper will also highlight the factor that will have the least influence on the adoption of HR analytics and thus can pave the way for further studies for effective contribution to the adoption of HR analytics. **Results:** The findings from this research have depicted that factors like tool availability, data availability, and individual-level adoptions are crucial and affect the adoption of HR analytics. The study also concluded with several managerial implications and future research directions, which will give further opportunities to researchers in the field of Human Resource Analytics.

Keywords— Human Resource Analytics, IT industry, Exploratory Factor Analysis, Human Resource Analytics Adoption.

INTRODUCTION

In this world of information, where all business entities want to build a competitive edge in the elevating global market (Kumar et al., 2020), the success of organizations depends on learning and adopting new processes and techniques in all business departments. The various internal and external forces have impacted businesses today in adopting new systems and technology; hence, this has increased pressure on human resources professionals to adopt new technologies to match the

increased competition and rapid economic development in the era of industry. An organization can achieve better progress by acquiring HR analytics (Raj & Lalhall, 2024) and various metrics and creating a competitive edge in society. Bondarouk (2017) has defined HR analytics as the "systematic identification and quantification of people drivers of business outcomes." According to Jain (2020), "HR analytics is the art of collating, categorizing and scrutinizing the data related to HR functions & using several types of software and analytical processes to ensure better

decision making within the organization to improve organizational performance."

Information technology (IT) encompasses computer hardware and software creation, application, and upkeep. IT-enabled services (ITES) are not core IT but rely on IT assistance (Afzal, 2019; Varun, 2020). Most of it involves soft communication skills where input of data is necessary. It is separated into three categories: legal process outsourcing (LPO), knowledge process outsourcing (KPO), and business process outsourcing (BPO). The IT industry depends heavily on its human resources. This skilled workforce gives this sector a competitive edge. Its creative work culture, which thrives on adopting new tools and applications like AI and HR Analytics, and its focus on competitiveness, strategic advantage, flexibility, and individualization make the IT-ITES sector the most vibrant by nature (Varun, 2020). Several factors aid in the adoption of HR analytics. However, other factors act as a hindrance to adoption (Shaik, 2023). This study tries to discover the most impactful factor that helps in HR analytics adoption in the IT industry.

LITERATURE REVIEW

Gentle (2015), in his study on 'the Provocation Series Paper,' posited that HR analytics is expected to have a significant negative impact on HR practitioners. Several experts on HRA comment that organizations must adapt to emerging technologies that are entering the market due to technological advancements and the growing use of big data (Afzal, 2019). However, due to many individual and organizational level factors, HR experts are hesitant to adopt these cutting-edge tools. Products available in the market, such as Oracle's Taleo talent management suite and SAP's Success Factor, provide features like consolidating many HR-related datasets into a single cloud-based data warehouse. Although costing the firms a significant amount of money, these tools can enable HR data to make strategic decisions and integrate them into other business areas (Angrave, 2016; Kumar, 2021). Therefore, examining the factors that may enable or may become resistance to adopting HRA becomes imperative. Different studies (Raj & Lalhall, 2024) (Raj et al., 2024), (Raj & Lalhall, 2024), on adopting HR analytics have categorized these into personal and organizational factors. A review of such studies and the categorization of the factors are as follows:

Personal factors

Self-efficacy

The foundation of self-efficacy (Albert, Self-efficacy: Toward a unifying theory of behavioral change, 1977) is the conviction that one can succeed and reach a specific performance level. Thus, one's confidence in one's abilities determines whether or not to embrace HRA. Tool availability is defined as having the skill

sets necessary to identify what data is needed and the capacity to analyze and understand data. Individuals with the requisite skill sets to use software to evaluate the essential dataset in the system are also equally vital (Johnson, 2011).

Quantitative self-efficacy

For the sake of this study, mathematical self-efficacy will be referred to as quantitative self-efficacy. People with higher levels of self-efficacy are more likely to participate in and do better on tasks that expand their knowledge and comprehension, supporting a more comprehensive learning process (Ozgen, 2013). Earlier research (Albert, 1982), (Schunk, 2014), and (Zimmerman, 2000) also supports the factor of quantitative self-efficacy affecting the adoption of HRA. Birigin (2009) and Ozgen (2013) presented similar ideas, stating that individuals who "had benefits and made life easier at work" also "believed that connections between mathematics and the real world increased their success in the workplace."

Individual level adoption

Innovations, in general, must be acknowledged for businesses to succeed in the current global environment and obtain a competitive advantage (Bersin, 2013; Giuffrida, 2013). Research indicates that both domestically and internationally, CEOs consider human resources among the most critical elements in establishing and preserving a competitive edge through analytics (Lesser & Hoffman, 2012; Financieras, 2013). A person goes through the adoption stage until they determine the time to institutionalize the innovation's use, put it to full use, and go on to the implementation stage. Alternatively, a person can choose not to move forward to passively reject the innovation or actively decide not to adopt it during the adoption procedure. The degree of adoption refers to the extent of the adoption procedure. An individual has made progress toward deciding whether or not to adopt the novel idea (Greenwood, 2018). Innovation adoption can be a complex process since it involves people participating in ways that can influence other people's decisions to accept or reject the innovation (Jeyaraj & Sabherwal, 2008). The willingness of an individual to adopt and use innovation can significantly impact a business's competitive advantage (Conrad, 2013).

Organizational factor

Tool availability

Tool availability is defined as having the skill sets necessary to identify what data is needed and the capacity to analyze and understand data. Software and system updates are also seen as crucial. More quickly and with greater data storage capacity, people can now access computers, and networks and connections have also improved. Thanks to modern

HRIS and enhanced technology, organizations now have a different perspective on capital management (Carlson & Kavanagh, 2011). Undoubtedly, the creation of the HR systems in use now should have taken advantage of the computers and infrastructures in use today (Carlson & Kavanagh, 2011).

Data availability

Data availability is the accumulated information maintained in the HR division and the company. According to (Carlson & Kavanagh, 2011), reporting and benchmarking are the two HR practices most frequently employed when metrics and workforce analytics are concerned with administrative process efficiency. HR systems must now be built with computers and available infrastructures (Carlson & Kavanagh, 2011). Reliable data relevant to important performance areas can give businesses essential insights. Human resources managers can use analytics to provide value to each process step, from hiring to retaining people. The selection of data sources and metrics is crucial since businesses need to know what to measure to evaluate business success (Kumar, 2021).

Objective

The primary goal of this study is to identify the factors that are most important in adopting HR analytics in human resource management. In addition, the study looks for significant problems and obstacles that arise when HR analytics are adopted in the IT industry.

Rationale of study

HR analytics is an innovative approach to enhance and utilize HR for organizational benefits. HR analytics has been embraced by the Western IT industry thus far, but it is also making inroads into the Indian IT sector as of late. The current study thoroughly examines HR analytics in the Indian IT industry and how it approaches the creation and use of analytics. Consequently, there is a great deal of promise for HR analytics in the Indian IT sector, but there are gaps in HR systems, teams, and people skills (Boudreau, 2017). Since we firmly believe that imaginative and creative minds can produce the most significant economies, having logical HR professionals on staff is essential for strategic decision-making and maintaining a competitive edge (Bondarouk, 2017). In order to guarantee that such talent exists within the company, we also require robust assessment tools.

METHODOLOGY

Research design

In this study, both descriptive and quantitative research methods were applied. A questionnaire designed in part using the UTAUT paradigm is used to collect the data. There are 25 questions in the questionnaire, some of which are based on organizational aspects and the UTAUT model, and others of which are meant to help understand the demographic profiles of the respondents. Only the Indian states were included in the study. This study is heavily field-based, with all the data used for analysis derived from survey responses obtained in the field. This study's unit of analysis is employees of the IT sector.

Sample frame

Since this research aims to examine responses from all over India, the Internet was thought to be the most practical and efficient way to collect data to save time and effort. In order to collect the answers, a Google Spread Sheet version of the survey was created and distributed via emails and several social media platforms. Over five to six months, 633 replies were collected, of which 596 were determined to be accurate and comprehensive. Thus, 596 people make up the study's sample size. The respondents were selected randomly from among the 29 states in India, and their demographic characteristics, including gender, age, and monthly income, were carefully considered. Both snowball sampling and convenience sampling were used to gather the data.

Brief Profile of Respondents

Table 1 displays the respondents' profiles. The respondents' demographic and economic characteristics are considered when tabulating the profiles. The study did not include the answers provided by those who declined to respond to this question.

Table 1

		FREQUENCY	PERCENTAGE
GENDER	FEMALE	220	36.91
	MALE	376	63.08
	TOTAL	596	100.0
AGE	Below 20	27	4.53
	20-30	368	61.74
	30-40	124	20.80

	40-50	63	10.57
	50-60	11	1.84
	Above 60	3	0.5
	Total	596	100.0
MONTHLY INCOME	ABOVE 50000	32	5.37
	10000-20000	82	13.76
	20000-30000	123	20.64
	30000-40000	197	33.05
	40000-50000	151	25.33
	Up to 10000	11	1.84
	Total	596	100.0
CHANNEL	AGENT	403	67.62
	ANY OTHER	0	0
	BRANCH OFFICE	24	4.03
	INTERNET	107	17.95
	BANK	62	10.40
	Total	596	100.0

Reliability Analysis

One of the main issues during the research process was ensuring the questionnaire was reliable. A trustworthy questionnaire is one that consistently measures the concept it is intended to measure. The reliability of the questionnaire utilized in a given study is demonstrated by the respondents' ratings staying relatively constant after multiple measurements. Cronbach (1951) developed the most widely used scale reliability metric, Cronbach α (alpha). As per Cronbach's (1984) assertion, one may assess a questionnaire's internal consistency and reliability by computing its Cronbach's α . According to Nunnally (1978), Cronbach's α , dependent on the number of variables/items in a questionnaire and the correlations between the variables, is considered the most significant measure of the account reliability index.

The Cronbach's alpha coefficient (α) is used to evaluate the index alpha. Following a comprehensive analysis of all 25 questions in the structured questionnaire, the overall questionnaire's α value was determined to be 0.805 (refer to Table 2). A Cronbach's α value of 0.7 or above indicates that a factor is regarded as dependable, according to Kline (1999). The internal consistency of the questionnaire is assessed as "good" because its $\alpha = 0.805$ value is within an acceptable range ($0.7 \leq \alpha < 0.9$ is judged good). The results imply that the structured questionnaire used in this study is reliable and has internal consistency.

Table 2

CRONBACH ALPHA	NO. OF ITEMS
0.806	25

Table 3.

KMO and Bartlett's Test

Kaiser–Meyer–Olkin measure of sampling adequacy		0.773
Bartlett's test of sphericity	Approximate chi-square	2,958.438
	df	253
	Significant value	0.000

Kaiser–Meyer–Olkin and Bartlett's Test

A measure of sample adequacy called Kaiser-Meyer-Olkin (KMO) and Bartlett's test of sphericity is advised to verify the data-to-variable ratio for the analysis being carried out. KMO and Bartlett's tests are crucial in most studies to approve the adequacy of the sample. According to Hutcheson and Sofroniou (1999), values between 0.5 and 0.7 are mediocre, values between 0.7 and 0.8 are good, values between 0.8 and 0.9 are great, and values beyond 0.9 are superb. Kaiser (1974) has indicated that a minimum of 0.5 is acceptable. Bartlett's test of sphericity evaluates the hypothesis that the correlation matrix is an identity matrix. This test must be significant, meaning its significance value should be less than 0.05. It follows that Bartlett's test of sphericity must always be less than 0.05 for factor analysis to be appropriate; otherwise, the data will not be deemed viable for use.

The Kaiser-Meyer-Olkin measure of sampling adequacy value for this dataset, according to KMO analysis, is 0.773 (Table 3), falling within the range of "good." As a result, the study's sample size is likely appropriate for factor analysis. Factor analysis is appropriate because Bartlett's test has also been determined to be highly significant (p

< 0.001). Significantly less than 0.05, at 0.000 (Table 3), is the value for this investigation. Therefore, this study easily satisfies the need to perform a factor analysis.

Principal Component Analysis

The underlying presumption of principle component analysis (PCA) is that all Variance is common. For this reason, every commonality is one before the extraction (Table 4, column 2). The commonalities in Table 4 (column 3) represent the common Variance. It can be challenging for a variable to load on any given component when its commonality is between 0.0 and 0.4. Table 4 demonstrates that the extracted communalities meet the requirements to be included in the factor solution. Except for Q25, where the value is 0.387, the values recovered following analysis fall between 0.409 and 0.696; nonetheless, as the value is so near to 0.4, this anomaly is not considered very relevant.

Items	Initial	Extraction
Q1. I have a full array of HR Analytics tools available at work if I choose to use them	1.000	0.630
Q2. I only have fundamental HR Analytics tools available at work if I choose to use them.	1.000	0.487
Q3. I am not sure if tool availability will aid in my working speed	1.000	0.489
Q4. I have had a lot of chances to experiment with several HR Analytics apps.	1.000	0.430
Q5. My organization's database has all the data I need to use HR Analytics software	1.000	0.689
Q6. My organization's HR system collects data from all HR interactions.	1.000	0.432
Q7. My organization has one database for all departments to use.	1.000	0.546
Q8. My organization's database has an interface that is compatible with other systems.	1.000	0.437
Q9. We use the same system/platforms for all HR activities.	1.000	0.428
Q10. My company is putting a policy in place to use HR Analytics	1.000	0.627
Q11. I am not required to HR Analytics.	1.000	0.431
Q12. The use of HR analytics is voluntary in my organization.	1.000	0.534
Q13 I am beginning to explore using HR Analytics.	1.000	0.568
Q14. I am interested in using HR Analytics	1.000	0.432
Q15. HR Analytics is convenient to use.	1.000	0.478
Q16.I think HR analytics can be easily applied.	1.000	0.478
Q17. I am able to use HR Analytics without much effort.	1.000	0.482
Q18. I am confident that I can use HR analytics efficiently.	1.000	0.587
Q19. I think I can perform better with the use of HR analytics.	1.000	0.469
Q20. I find using mathematical and/or statistical measurements interesting.	1.000	0.487
Q21. I worry about my capacity to solve mathematical and/or statistical challenges.	1.000	0.469
Q22. When I utilize statistics or math, I get anxious	1.000	0.421
Q23. I like using statistical and mathematical metrics in my work	1.000	0.454
Q24. I find statistical and mathematical measurements difficult	1.000	0.387
Q25. I become nervous while using statistics at work place.		

Table 4.

After the values were retrieved in PCA, it was discovered that the first three factors or components in the initial solution table had an eigenvalue more significant than 1, meaning that they validated the majority of the observed variation in developing workers' views regarding the adoption of HR analytics (Table 5). Factors with less than one would not be considered when determining how the study should be interpreted, as the Kaiser criterion specifies that only factors with eigenvalues more significant than one should be regarded as primary factors. Tabachnick and Fidell (2007) state that PCA is a statistical tool for data reduction used to extract each component's maximum Variance from a dataset. Dividing them into smaller, more manageable components simplifies the researchers' usage of enormous quantities of variables. Before employing a "true" factor analysis method, the researchers use PCA to minimize or mine the data.

The factors are then rotated using the Varimax with Kaiser normalization approach for better understanding because the unrotated factors are highly confusing and difficult to understand.

Factor loading has been used to quantify the association between the factors and the variables. Loading numbers near 1 suggests a strong correlation between the variable and the factor, while loading values closer to 0 indicate a

poor correlation. As a result, for interpretation, only factors with values less than 0.4 are considered; those with values more than 0.4 are considered inconsequential. Five component or factor groupings could be identified from a thorough analysis of Table 5's total Variance explained, which included twenty-five items. Before rotation, the component matrix is shown in Table 6.

The loadings of every variable onto every factor are contained in this matrix. Table 7 provides further clarity on the factor structure's rotation, which aids in comprehending and identifying the affecting factors. According to Dutta, 2019 The factor transformation matrix, which shows how much the factors were rotated to get a solution, is the last component of the result (Table 8).

Table 5. Total Variance Explained (Extraction Method: Principal Component Analysis)

Component	Initial Eigenvalues			Extraction Sums of Square Loading			Rotation Sums of Square Loading		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.685	20.921	20.921	5.324	23.935	23.935	3.645	18.312	18.312
2	2.237	9.567	29.663	2.235	9.650	33.567	2.931	11.121	32.456
3	1.637	7.121	36.678	1.634	7.112	41.786	2.530	10.865	42.321
4	1.234	5.456	42.141	1.211	5.325	46.121	1.823	9.076	52.346
5	1.145	4.865	47.124	1.146	4.987	51.117	1.713	8.456	61.567
6	0.996	4.347	56.780						
7	0.985	4.336	59.188						
8	0.976	4.275	60.453						
9	0.943	4.214	64.664						
10	0.865	3.732	68.389						
11	0.814	3.556	71.941						
12	0.743	3.394	78.345						
13	0.667	3.023	80.321						
14	0.654	2.923	82.342						
15	0.677	2.853	84.764						
16	0.532	2.432	86.431						
17	0.532	2.345	87.045						
18	0.435	2.156	87.132						
19	0.443	2.132	88.112						
20	0.467	2.098	89.213						
21	0.421	2.078	91.210						
22	0.418	2.008	93.227						
23	0.367	1.786	95.783						
24	0.324	1.573	98.431						
25	0.311	1.432	100.000						

Table 6. Component Matrix

	1	2	3	4	5
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Q1	0.214	0.466	0.497	0.336	-0.126
Q2	0.136	0.532	0.227	-0.489	0.109
Q3	0.371	0.654	-0.034	-0.204	-0.058
Q4	0.510	0.524	-0.264	-0.068	-0.156
Q5	0.348	0.568	0.456	0.176	-0.180
Q6	0.646	0.086	-0.076	-0.178	-0.186
Q7	0.656	0.034	0.063	-0.564	-0.306
Q8	0.548	-0.034	0.134	-0.345	0.324
Q9	0.546	-0.243	0.167	-0.243	-0.300
Q10	0.565	-0.043	0.253	-0.231	0.465
Q11	0.421	-0.435	0.121	-0.054	0.134
Q12	0.474	0.235	-0.243	-0.045	0.123
Q13	0.479	-0.456	0.067	0.129	-0.134
Q14	0.398	-0.345	0.134	0.056	0.064
Q15	0.475	0.132	0.056	0.450	0.145
Q16	0.429	0.345	-0.078	0.332	0.341
Q17	0.532	0.202	-0.062	0.245	-0.289
Q18	0.432	0.337	-0.342	0.224	-0.356
Q19	0.487	0.059	-0.346	0.233	0.302
Q20	0.398	-0.376	-0.278	-0.089	-0.098
Q21	0.576	-0.207	-0.435	0.002	-0.070
Q22	0.561	0.044	-0.434	-0.049	-0.203
Q23	0.300	0.137	-0.376	0.303	0.302
Q24	0.232	0.245	0.187	0.204	0.423
Q25	0.521	0.355	0.049	0.230	0.234

Table 7. Rotated Component Matrix

	Component				
	1	2	3	4	5
Q1	0.086	-0.032	-0.056	0.034	0.782
Q2	-0.001	-0.053	-0.019	0.671	0.167
Q3	-0.278	0.075	0.276	0.586	0.361
Q4	-0.234	0.348	0.365	0.234	0.390
Q5	-0.023	0.018	0.136	0.376	0.745
Q6	0.156	0.338	0.127	0.432	0.210
Q7	0.387	0.128	-0.042	0.581	-0.031
Q8	0.475	0.321	0.167	0.342	-0.047
Q9	0.465	0.296	-0.089	0.365	-0.019
Q10	0.654	-0.029	0.347	0.217	0.048
Q11	0.617	0.128	-0.012	0.057	-0.003
Q12	0.602	-0.045	0.102	0.006	0.061
Q13	0.442	0.401	-0.087	-0.308	0.124
Q14	0.437	0.387	0.005	-0.065	0.056
Q15	0.276	0.192	0.465	-0.078	0.451
Q16	0.054	-0.201	0.653	0.156	0.128
Q17	0.024	0.074	0.364	0.067	0.032
Q18	0.271	0.165	-0.041	-0.106	0.167
Q19	0.165	0.320	0.634	0.043	-0.129
Q20	0.278	0.659	0.021	-0.002	-0.113
Q21	0.061	0.709	0.278	0.003	-0.003
Q22	-0.052	0.562	0.254	0.156	0.007
Q23	0.041	0.276	0.530	-0.018	0.021
Q24	-0.005	-0.078	0.329	0.065	0.038

Q25	-0.065	0.217	0.007	0.007	0.210
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Table 8. Component Transformation Matrix

Component	1	2	3	4	5
1	0.432	0.564	0.367	0.347	0.231
2	-0.561	-0.287	0.365	0.467	0.504
3	0.528	-0.541	-0.478	0.278	0.487
4	0.021	-0.132	0.387	-0.765	0.323
5	0.456	-0.437	0.559	0.056	-0.309

Discussion

Following extensive analytical observation, it was determined that adopting HR Analytics in the IT business is primarily influenced by three out of five aspects. Each element is described separately, chronologically, according to priority.

Organizational Factors

Tool availability

Availability of tools was the highest-ranked component that affected the adoption of HR analytics in the IT industry. Table 5 shows that the first component, the availability of tools, has the highest eigenvalue, 4.686. For the adoption of HR analytics in the IT industry, the availability of tools is essential as it helps the organization to adapt to changes in technology and upgrade itself to fit in with emerging trends and technology, as well as gain a competitive edge. Adopting HR analytics depends on the availability of tools (Afzal, 2019). The findings show that the IT industry should make tools viable for employees to work with (Kremer, 2018). The employees should be responsive and receptive while interacting with the analytical applications. They should be eager to use the tools and make tasks more effective (Mittal, 2021).

Data availability

Once the company's dataset has the necessary data, the availability of HR tools becomes essential (Afzal, 2019). As per Table No. 5, the second component, which has a value of 2.237, is data availability. Data availability makes it easier to work with, making the tasks effective (Bowiva, 2017; Giuffrida, 2013). The

organization should work on gathering, storing, and using data through datasets datasets for further decisions so data availability influences data availability influences the adoption of HR analytics.

Personal Factors

Individual Level Adoption

The third most important factor under Personal Factor classification in Table No. 5 with Eigenvalue 1.6 is individual-level adoption. Different studies have shown that although data and tools are available in the organization, adoption still needs to be improved (Mittal, 2021; Afzal, 2019). Also, some studies suggest that the adoption of HR analytics at the individual level is significant (Greenwood, 2018). Despite the availability of tools and data the organizations need to inculcate the instinct of adopting HR Analytics at individual levels (Vicente Fernandez, 2020).

Self-Efficacy and Quantitative Self-efficacy

The other two factors in personal factors, namely self-efficacy and quantitative self-efficacy, also depicted lower eigenvalues of 1.234 and 1.145, respectively, from Table No. 5. This value is also significant. It can be considered as the factor that influences the adoption of HRA, as the impact of self-efficacy and quantitative self-efficacy can be seen in various papers. Various authors (Albert, 1982; Chau, 2001; Ozgen, 2013) have also mentioned in their studies that self-efficacy is an important factor for adopting HR analytics.

Conclusion

In this research, it has been noted that the availability of tools is the most influential factor, followed by data availability and individual-level adoption. With accessible data and tools within an organization, individual adoption becomes significantly more accessible and convenient (Greenwood, 2018). Organizations should invest additional efforts in building employees' self-belief and confidence in their ability to utilize quantitative methods (Ozgen, 2013). Employees must have a clear and positive perception regarding the use of analytics in the HR department. Additionally, organizations should ensure that resources are readily available to employees to facilitate efficient work and the adoption of new technologies.

Considering the rapid advancements in technology, tools, and techniques, the HR department of the IT industry must embrace HR analytics in order to attain a competitive advantage (Kumar, 2021).

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