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HR Analytics Adoption in India - A Sector Wise Study

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ABSTRACT

Human Resource (HR) Analytics has emerged as a transformative a tool for improving strategic planning and decision-making within organizations. This study examines HR Analytics in India by conducting a sector-wise analysis, with a particular emphasis on the IT, Financial, Manufacturing, and Retail. The objective of this research is to offer an exhaustive analysis of the ways in which various industries utilize HR Analytics to enhance workforce management and optimize organizational performance. Furthermore, it endeavors to identify sector-specific best practices and obstacles associated with the implementation of HR Analytics. Findings are expected to provide organizations that are interested in improving their HR strategies through data-driven approaches with valuable insights.

Keywords: HR Analytics, Adoption factors, IT Sector, Financial Services, Manufacturing Sector, Retail Sector

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INTRODUCTION

The voyage of HR analytics in India is indicative of a more general global trend towards data-driven human resource practices. In the past, Indian organizations primarily relied on conventional HR methods that prioritized manual record-keeping and fundamental employee metrics. Nevertheless, the emergence of sophisticated technologies and data analytics has resulted in a substantial transition towards the utilization of data to inform HR strategies. In the early 2000s, the rapid expansion of the Information Technology (IT) sector and the growing adoption of digital tools in India marked the beginning of the evolution of HR analytics. Initially, HR analytics was mainly adopted by large IT companies that leveraged technology for performance monitoring and workforce management, setting a benchmark for other sectors. These early adopters showcased the importance of data in enhancing HR processes and achieving business objectives. HR analytics has transformed employee engagement strategies and talent acquisition in the IT sector. Data has been utilized by IT companies to predict attrition, identify skill deficits, and develop targeted development programmes (P. Sharma & Khan, 2023) The financial services, which is known for its data-intensive nature, has also adopted HR analytics to improve its HR functions. Financial institutions and banks have begun implementing analytics to manage large recruitment campaigns, assess employee performance, and ensure compliance with regulatory standards. The need to improve workforce productivity and operational efficiency has led various sectors, particularly manufacturing and retail, to embrace HR analytics. In manufacturing, analytics plays a vital role in managing shift schedules, reducing absenteeism, and monitoring employee performance. This recognition of data's importance has driven a shift towards aligning HR functions with broader organizational goals.The retail sector in India, which has undergone substantial growth and modernization, is employing HR analytics to resolve the challenges associated with workforce management and customer service (Cayrat & Boxall, 2023). Overall, the increasing adoption of HR analytics across various sectors represents a shift towards optimizing HR functions and leveraging data to drive better business outcomes in India. Each of these sectors faces unique challenges in managing diverse workforces and delivering high-quality services, making data analytics particularly valuable.

Overall, HR analytics in India has evolved from a niche practice to a fundamental strategic tool employed across multiple industries. The growing recognition of data as an essential asset in human resource management is evident in the adaptation of analytics tailored to the specific needs of each sector. As organizations continue to navigate the complexities of the modern workforce, HR analytics will become more crucial in the development of effective HR strategies and the promotion of business success as organizations continue to navigate the intricacies of the contemporary workforce (Olufunke Olawale et al., 2024).

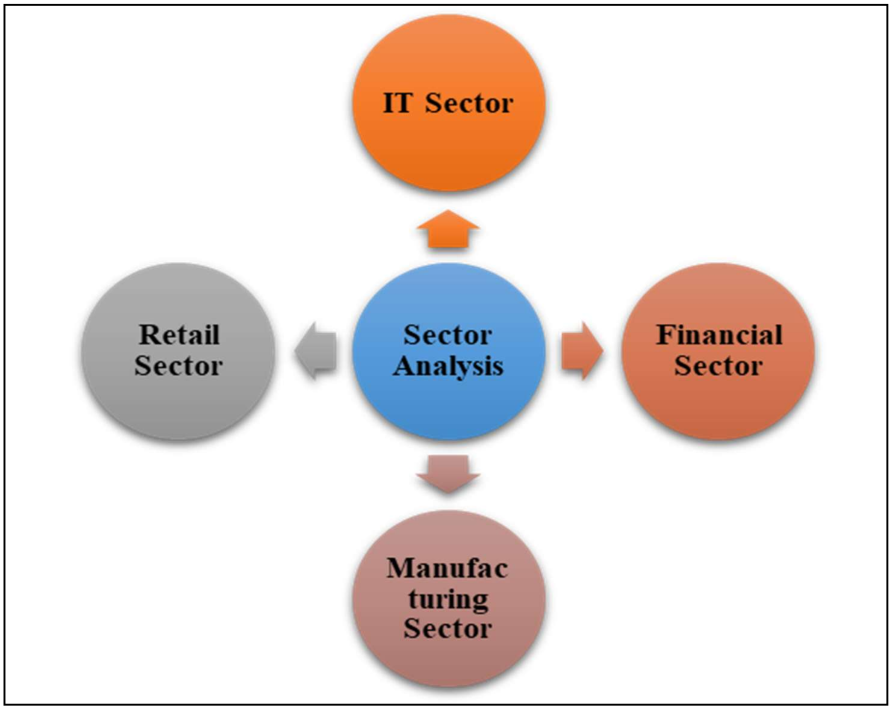

Fig. 1: Sector Analysis of HR analytics adoption

1.1 Introduction to HR Analytics and Its Importance

HR analytics leverages data analysis tools to enhance HR functions and decision-making, moving from traditional methods to sophisticated predictive models (Selvaraj, 2023). Initially focused on descriptive analytics, modern HR analytics now includes predictive and prescriptive analytics, offering insights into employee engagement, retention, recruitment, and performance management (Rigamonti et al., 2024). These tools are crucial for aligning workforce strategies with business goals, optimizing HR processes, and improving employee performance (Tuli et al., 2018; D. Sharma, 2020).

Sector-Specific Applications:

Information Technology (IT): HR analytics is vital for talent acquisition, attrition prediction, and performance management, helping IT firms stay competitive and adapt to industry changes (Gope et al., 2018; Kolasani, 2023).

Manufacturing: Analytics optimizes workforce allocation, identifies talent gaps, and enhances operational efficiency, improving productivity and safety compliance (Popo – Olaniyan et al., 2023). Manufacturers can monitor safety compliance, streamline workforce planning, and implement targeted training programs with the assistance of analytics tools. This ultimately contributes to a more effective and secure working environment by resulting in improved productivity.

Financial Services: HR analytics ensures regulatory compliance, optimizes talent management, and enhances employee engagement, leading to better performance and efficient HR processes (Jafri, 2020). This ensures that organizational objectives are efficiently attained, compliance standards are met, and HR practices are enhanced. Financial services can enhance their operational efficiency, resolve obstacles in advance, and optimize their workforce management through the implementation of analytics.

Retail: Retail is distinguished by seasonal fluctuations in demand and high employee turnover. By optimizing staff allocation, administering workforce scheduling, and enhancing employee retention strategies, HR analytics is instrumental in resolving these issues (Etukudo, 2019). Retail organizations can more effectively manage seasonal fluctuations, guarantee sufficient personnel levels, and mitigate attrition rates by leveraging data-driven insights. This leads to enhanced customer service, more efficient personnel administration, and the capacity to effectively address the obstacles of high staff attrition and fluctuating demand (Hughes & Rog, 2008).

1. LITERATURE REVIEW

1.1 Transformative Impacts and Adoption Challenges of HR Analytics Across Sectors in India

The literature on HR analytics demonstrates its significant impact on human resource practices across various sectors in India. This review compiles research findings to provide a comprehensive understanding of HR analytics' adoption, evolution, and sector-specific applications, along with the challenges faced during implementation. Aggarwal et al. (2021) explored the impact of company characteristics on HR disclosure practices in Indian public sector enterprises. They developed the Human Resource Disclosure Index (HRDI) and found that market capitalization and ownership concentration significantly influenced HR disclosure, while other variables had negligible associations. Ramachandran (2023) analyzed the adoption of HR analytics in the Indian IT sector, revealing a positive correlation between employee satisfaction and the perception of HR analytics tools. Jauhari (2021) focused on IT Fortune 500 companies, demonstrating how HR analytics tools enhance HR management efficacy and identifying factors that influence their adoption. Similarly, Harshita Agarwal et al. studied the adoption of HR analytics in Indian IT and ITES organizations, identifying key factors that influence change acceptance and laying a foundation for future research in HR analytics. Mathur (2023) examined the adoption challenges of HR analytics among HR professionals in manufacturing firms in Haryana. The study highlighted the benefits of data-driven decision-making and the obstacles to effective implementation. Selvaraj et al. (2023) investigated the role of HR analytics in enhancing organizational sustainability within IT companies. Using AMOS and SPSS for data analysis, their research showed a substantial correlation between HR analytics and HRM practices, validating a novel methodological approach for predicting organizational outcomes. Jaikumar et al. (2015) discussed the challenges faced by the Indian retail industry in incorporating HR analytics with store operations. They compared Indian practices with those of global retail giants, identifying deficiencies and offering recommendations for improvement. Jain et al. (2020) explored the integration of HR analytics into the corporate environment, emphasizing its ability to replace outdated manual processes. The study assessed the application, constraints, and metrics for evaluating organizational suitability for HR analytics adoption. Sharma et al. (2022) reviewed the role of HR analytics in improving organizational decision-making during the pandemic. They emphasized its significance in strategic planning, cost management, and revenue generation. Ameer et al.

(2022) investigated the behavioral intentions that motivate HR professionals to implement HR analytics, using PLS-SEM to validate influencing factors. They found that performance expectancy and facilitating conditions positively impacted adoption, while fear appeals hindered it.

Nagpal et al. (2022) discussed the importance of data-driven decision-making in the context of Industry 4.0. They identified critical HR analytics factors—predictive, descriptive, and prescriptive—that enhance employee well-being and influence decision-making in institutions. The reviewed literature collectively highlights the increasing importance of HR analytics across various sectors in India. While the IT and public sectors exhibit higher adoption rates, other industries face challenges that need to be addressed. The research underscores the necessity of strategic implementation and understanding sector-specific dynamics to effectively leverage HR analytics.

Table 2.1 HR Analytics Studies Sector and Focus

Author (s)	Year	Sector	Key Focus	Methodology
Nayak et.al	2024	IT	Simplification of HR analytics for data collection, measurement, and forecasting, focusing on employee attrition.	Literature review using secondary data from various sources.
Mahendran et.al	2024	Manufacturing	Barriers and solutions for HR analytics implementation in Chennai's manufacturing sector.	Literature review, demographic data, and correlation analysis.
Agarwal et.al	2022	Financial Services	Impact of HRM practices on employee satisfaction and performance in the Financial Services.	Literature review and analysis of HRM practices.
Krithika et.al	2022	Manufacturing	Role of technological factors in HR analytics adoption in manufacturing industries.	Survey of 150 HR professionals in southern India.
Saritha et.al	2023	IT	Relationship between HRM practices and company performance in the IT-ITES sector.	Mixed-method: qualitative interviews and quantitative surveys.
Prasad et.al	2018	Retail	Employee engagement factors in the retail sector of Jharkhand.	Pilot study using structured questionnaires and SPSS analysis.

Kumar et.al	2023	Retail	Challenges and trends in HR management across the Indian retail sector.	Review of retail sector HR practices and trends.
Afzal et.al	2023	IT	Adoption and potential of HR analytics in the Indian IT sector, focusing on HR systems and skill gaps.	Literature review and analysis of HR-analytics adoption.

Prepared by authors

The impact of recent HR analytics studies in India from 2018 to 2024 is summarized in the table, which pertains to a variety of sectors, including banking, retail, IT, and manufacturing. It encompasses research on the function of HR analytics in enhancing employee engagement, productivity, and decision-making. The aggregate findings of the studies emphasize the increasing significance of HR analytics in overcoming sector-specific challenges to which sectors with advanced HR analytics outperform those with limited analytics adoption.

2.3 Hypothesis Development:

Fig. 2: Proposed Model for the Study

Prepared by Authors

2.3.1. Adoption of factors

The factors that influence the incorporation of HR Analytics across various sectors in India must be analyzed when investigating its adoption. These factors typically encompass employee training, leadership support, technological preparedness, and organizational culture. These elements can vary substantially between sectors, which can affect the level and efficacy of HR Analytics adoption, as indicated by previous research(Fernandez & Gallardo-Gallardo, 2021). A sector with a greater degree of technological infrastructure may experience a more seamless integration of HR Analytics than one with limited technological resources, for instance. Sectors that emphasize leadership support and employee development may exhibit more sophisticated adoption practices. As a result, it is suggested that:

H1: There is a significant difference in various HR Analytics adoption factors across different sectors in India.

This hypothesis aims to investigate the impact of sector-specific characteristics on the adoption and implementation of HR Analytics. It has the potential to provide valuable insights into sectoral distinctions and to guide targeted strategies for effective adoption. The extent and effectiveness of HR Analytics implementation are considerably influenced by a number of important factors when examining their adoption across various sectors in India. These factors consist of Performance Expectancy, Social Influence, Organization Support, Tool Availability, and Effort Expectancy. Each is essential in determining the manner in which various sectors integrate HR Analytics into their operations (Irunna Ejibe et al., 2024).

1. *Effort Expectancy* - Effort Expectancy refers to the perceived ease or difficulty of using HR Analytics tools (Beba & Saatcioglu, 2009). Sectors with technical workforces may find the transition to HR Analytics easier compared to those with lower technical proficiency, highlighting the need for customized training and support.
2. *Tool Availability* - Tool Availability pertains to the accessibility of HR Analytics tools, influenced by factors like technological infrastructure and budget constraints (Mata et al., 2022). Sectors such as finance and IT typically have better access to advanced tools compared to those with limited financial resources.
3. *Organization Support* - Organization Support measures leadership and management's backing for HR Analytics adoption. Sectors with proactive leadership and a data-driven culture are more likely to succeed in integrating HR Analytics (Orusa-Ejo & Joy Amina, 2018).
4. *Social Influence* - Social Influence encompasses external factors such as industry trends and peer practices. Sectors where HR Analytics is standard practice or where there is significant industry pressure show higher adoption rates (Bag et al., 2021).
5. *Performance Expectanc***y** **-** Performance Expectancy involves the expected benefits and performance improvements from HR Analytics adoption. Sectors that see a direct correlation between business outcomes and analytics, like retail and manufacturing, are more enthusiastic

   about adoption. The effectiveness and pace of HR Analytics adoption across various sectors are significantly influenced by each of these factors (Srinivas et al., 2024).

The reviewed literature emphasizes the importance of sector-specific dynamics in HR Analytics adoption in India. Higher adoption rates in the IT and finance sectors contrast with challenges in other sectors, underscoring the need for strategic implementation and understanding sector-specific factors to fully leverage HR Analytics.

2.3.2 Employment Performance

Recent research has highlighted the substantial potential of data-driven HR practices to boost organizational outcomes, emphasizing the role of HR analytics in enhancing employee performance. HR analytics involves the application of statistical methods and data analysis techniques to gain insights into employee performance (Fanisi, 2024). This approach enables organizations to systematically track and evaluate key metrics such as productivity, engagement, and retention. For example, analyzing productivity data can help identify high-performing employees and areas needing improvement. Engagement metrics can reveal how motivated and committed employees are, while retention data helps understand employee turnover patterns. The benefits of employing HR analytics include the ability to design more targeted interventions that address specific issues, ultimately leading to better performance outcomes. Based on these insights, we propose the following hypothesis:

H2: There is a significant correlation between HR Analytics adoption and employee performance across different sectors in India.

The use of HR analytics positively correlates with improved organizational outcomes by enhancing employee performance through targeted interventions and optimized resource allocation. This hypothesis suggests that organizations utilizing HR analytics are more likely to achieve superior performance results due to their ability to make data-driven decisions that address the unique needs of their workforce(GOOD, 2015).

2.2 Adoption Factors for Analytics Tools Across Various Sectors

Table 2.2 Comparison table of Adoption Factors for Analytics Tools Across Various Sectors

Factor	IT Sector	Financial Services	Manufacturing Sector	Retail Sector	Other Sectors
Effort Expectancy	Low complexity due to technical proficiency. Training may be required for new tools.	Low complexity; often high technical skills. Training programs are common.	High complexity; less technical expertise. Requires extensive training and support.	Moderate complexity; varies by company size and tech adoption.	Varies widely; often requires tailored training and support.
Tool Availability	High availability of advanced analytics tools.	High availability; well-funded and technologically advanced.	Limited availability due to budget constraints.	Moderate availability; may have outdated or basic tools.	Varies; often limited in smaller organizations or sectors with fewer resources.
Organization Support	Strong support from leadership; data-driven culture prevalent.	Strong leadership support; data-driven decision-making is a norm.	Less support; traditional practices dominate.	Varies; some companies support analytics, others stick to conventional methods.	Varies; sectors with less focus on data may struggle with support.
Social Influence	High influence from industry standards and peers.	High influence; industry benchmarks push for analytics adoption.	Low influence; industry norms still favor traditional practices.	Moderate influence; pressure from competitors varies.	Variable; influenced by industry trends and competitive pressures.

Performance Expectancy	High expectation of improved performance and competitive advantage.	High expectation; significant impact on financial performance.	Moderate expectation; potential for improvement recognized but not always realized.	Moderate to low expectation; benefits are recognized but not always acted upon.	Varies; sectors with clear performance links see higher adoption.

Prepared by Authors

The analysis across various sectors reveals distinct patterns in how different factors influence the adoption of analytics tools.

Effort Expectancy varies significantly across sectors. IT and Financial sectors experience low complexity due to high technical proficiency and established training programs. Manufacturing faces high complexity due to less technical expertise and extensive training needs, while Retail's complexity is moderate, depending on company size and tech adoption. Healthcare and Education sectors show varied effort expectancy, requiring tailored training.

Tool Availability is highest in the IT and Financial sectors, where advanced analytics tools are widely accessible (Manyika et al., 2011). The Manufacturing sector, constrained by budget limits, has less access to advanced tools, while the Retail sector's tool availability is moderate and can include outdated or basic tools. For other sectors, tool availability varies significantly, often limited in smaller organizations or those with fewer resources.

Organization Support is strong in IT and Financial sectors with a data-driven culture. Manufacturing shows less support due to traditional practices, while Retail's support varies by company.

Social Influence impacts sectors differently. IT and Financial sectors are highly influenced by industry standards and peer practices, leading to high adoption rates. Manufacturing has low influence due to traditional practices, while Retail experiences moderate influence from competitive pressures.

Performance Expectancy is highest in IT and Financial sectors, driven by expected improvements and competitive advantages. Manufacturing recognizes potential improvements inconsistently, while Retail's expectations are moderate to low.

Overall, analytics adoption across sectors is influenced by technical complexity, tool availability, organizational support, social influence, and expected performance improvements. IT and Financial sectors show stronger adoption due to favourable conditions, while Manufacturing and Retail sectors exhibit more variability due to unique challenges and resource constraints.

2. METHODOLOGY

The application and effectiveness of HR analytics in India's various industries are the focus of this investigation. HR specialists who are presently employed in significant enterprises across various industry sectors comprise the target population. In this study, large enterprises are defined as those with a workforce of 500 or more, which is indicative of their ability to implement comprehensive HR analytics systems.

Table 3.1 Total Sample Details

	Sector	N
Type of analytics	IT	187
	Financial Services	66
	Manufacturing	67
	Retail	80
	Others	24
	Total	424

Prepared by Authors

The application and effectiveness of HR analytics in India's various industries are the focus of this investigation. HR specialists who are presently employed in significant enterprises across various industry sectors comprise the target population. A total of 424 HR professionals were surveyed in order to acquire a representative sample(Kehoe & Wright, 2013). These professionals were distributed across five major sectors: IT, Financial Services, Manufacturing, Retail, and Others. The proportion of HR personnel in each sector was used to determine the sample size, as illustrated in the Table. In particular, the sample comprised 187 professionals from the IT sector, 66 professionals from financial services, 67 professionals from manufacturing, 80 professionals from retail, and 24 professionals from other sectors.

Table 3.2 Reliability Statistics

Factor	Cronbach's Alpha
Adoption Factor	0.946
Employment Performance	0.930

Basis the data analysis

Furthermore, regression analysis and correlation analysis were implemented to investigate the relationships between various variables and their influence on the implementation of HR analytics. The research's validity was further substantiated by consulting with subject matter experts and devising the questionnaire in accordance with established literature. This method guaranteed that the survey instrument accurately measured the intended constructs and generated reliable and valid data to support the study's objectives.

3. DATA ANALYSIS AND RESULTS

4.1 Descriptive statistics

The descriptive statistics reveal varied perceptions of HR analytics across different functions. Factors like simplicity of use (2.99), provided solutions (2.99), and resolution capabilities (2.95) show moderate approval. Higher mean scores are noted for norms of interest (3.36), learning (3.04), and performance (3.14). However, value (2.51) and permission (2.54) are less favorable. Employee performance indicators, such as quality (3.67), proficiency (3.75), and efficiency (3.91), score higher, suggesting positive influence by HR analytics. Overall, while some areas show positive engagement, others highlight challenges and variability in implementation and acceptance.

4.2 Hypotheses Testing

The research hypotheses are tested in this study using correlation and regression analysis.

4.2.1 Correlation analysis

Correlation is a measure of degree of relationship between the factors. It indicates how changes in one variable are related to changes in another variable. It ranges from -1 to +1.

Below table 4.1, provides the correlation between 5 extracted factors: Effort expectancy, Tool availability, Organization support, social influence and Performance expectancy.

Table 4.1 Correlations: (Group number 1 - Default model)

			Estimate
Effort_Expectancy	<-->	Tool_Availability	0.357
Effort_Expectancy	<-->	Organization_Support	0.515
Effort_Expectancy	<-->	Social_Influence	0.451
Perfromance_Expectancy	<-->	Effort_Expectancy	0.492
Tool_Availability	<-->	Organization_Support	0.523
Tool_Availability	<-->	Social_Influence	0.623
Perfromance_Expectancy	<-->	Tool_Availability	0.332
Organization_Support	<-->	Social_Influence	0.428
Perfromance_Expectancy	<-->	Organization_Support	0.559
Perfromance_Expectancy	<-->	Social_Influence	0.28

Interpretation: The correlation table indicates moderate to strong relationships between the latent variables involved in HR analytics adoption. Effort Expectancy shows moderate correlations with Organization Support (0.515), Social Influence (0.451), and Tool Availability (0.357). Performance Expectancy has significant positive relationships with Effort Expectancy (0.492) and Organization Support (0.559), and moderate correlations with Tool Availability (0.332) and Social Influence (0.280). Tool Availability is highly correlated with Organization Support (0.523) and Social Influence (0.623). The connection between Organization Support and Social Influence is modest (0.428). These correlations highlight the interconnectedness of these factors in HR analytics adoption.

Table 4.2 Correlation between Employment performance and Adoption Factor for different sectors

Correlations							
Sector			Effort_Expectancy	Tool_Availability	Organization_Support	Social_Influence	Perfromance_Expectancy
IT	Employee_Performance	Pearson Correlation	-0.009	.343**	-0.013	.273**	.527**
		Sig. (2-tailed)	0.901	0	0.864	0	0

		N	187	187	187	187	187
Financial Services	Employee_Performance	Pearson Correlation	-.453**	.465**	-0.196	.551**	.539**
		Sig. (2-tailed)	0	0	0.115	0	0
		N	66	66	66	66	66
Manufacturing	Employee_Performance	Pearson Correlation	0.092	.370**	0.026	.346**	.601**
		Sig. (2-tailed)	0.457	0.002	0.836	0.004	0
		N	67	67	67	67	67
Retail	Employee_Performance	Pearson Correlation	-0.137	.561**	-0.145	.511**	.721**
		Sig. (2-tailed)	0.227	0	0.198	0	0
		N	80	80	80	80	80
Others	Employee_Performance	Pearson Correlation	-0.086	0.34	0.135	0.088	.664**
		Sig. (2-tailed)	0.691	0.105	0.53	0.683	0
		N	24	24	24	24	24

Interpretation: The correlation table shows the sector-wise relationship of the Employee performance with the five factors of adoption. For IT sector, Employee performance has positive correlation with the Tool availability, social influence and Performance expectancy. Whereas, there is no correlation of Employee performance with Effort expectancy and Organization support. For Financial services, Employee performance has negative correlation with Effort expectancy and positive correlation with the Tool availability, social influence and Performance expectancy. Whereas, there is no correlation of Employee performance with Organization support. For Manufacturing and Retail sector, Employee performance has positive correlation with the Tool availability, social influence and Performance expectancy. Whereas, there is no correlation of Employee performance with Effort expectancy and Organization support. For other sector, Employee performance has positive correlation with the Performance expectancy. Whereas, there is no correlation of Employee performance with Effort expectancy, Tool availability, social influence and Organization support.

Squared Multiple Correlations:

The squared multiple correlation measures the proportion of variability in an observed variable explained by their factors.

4.2.2 Regression analysis

The regression coefficient represents the magnitude and direction of the association between the predictor (independent) variable and the outcome (dependent) variable.

Below table 4.3, provides the details of association of factors Effort expectancy, Tool availability, Organization support, social influence and Performance expectancy with the various adoption factors.

Table 4.3: Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
AF_Enjoyment	<---	Effort_Expectancy	1				
AF_Skillfulness	<---	Effort_Expectancy	0.95	0.034	27.571	***	par_1
AF_Preference	<---	Effort_Expectancy	0.988	0.028	35.017	***	par_2
AF_Solutions	<---	Effort_Expectancy	0.919	0.035	26.258	***	par_3
AF_Learning	<---	Effort_Expectancy	0.929	0.035	26.498	***	par_4
AF_Resolution	<---	Effort_Expectancy	0.951	0.037	25.602	***	par_5
AF_Interest	<---	Effort_Expectancy	0.78	0.039	19.935	***	par_6
AF_Ease	<---	Effort_Expectancy	0.761	0.036	21.198	***	par_7
AF_Permission	<---	Tool_Availability	1				
AF_Availability	<---	Tool_Availability	1.094	0.049	22.366	***	par_8
AF_Trial	<---	Tool_Availability	1.122	0.046	24.309	***	par_9
AF_Data	<---	Tool_Availability	0.948	0.054	17.484	***	par_10
AF_Collection	<---	Tool_Availability	1.05	0.061	17.114	***	par_11
AF_Leadership	<---	Organization_Support	1				
AF_Support	<---	Organization_Support	1.056	0.035	29.748	***	par_12
AF_Investment	<---	Organization_Support	0.936	0.037	25.553	***	par_13
AF_Influence	<---	Social_Influence	1				
AF_Importance	<---	Social_Influence	0.977	0.036	26.872	***	par_14
AF_Efficiency	<--	Perfromance_Expectanc	1				

	-	y					
AF_Effectiveness	<---	Perfromance_Expectancy	0.898	0.027	33.346	***	par_15
AF_Performance	<---	Perfromance_Expectancy	0.88	0.026	33.741	***	par_16

Interpretation: The table indicates that all designated connections (paths) between the latent variables and their observable variables in the SEM model are statistically significant. The critical ratios (C.R.s) exceed the threshold of 1.96, and the p-values are denoted as "***", indicating significant statistical significance for each path. Consequently, the hidden variables (Effort Expectancy, Tool Availability, Organization Support, Social Influence, Performance Expectancy) exert a noteworthy positive influence on their corresponding observable variables.

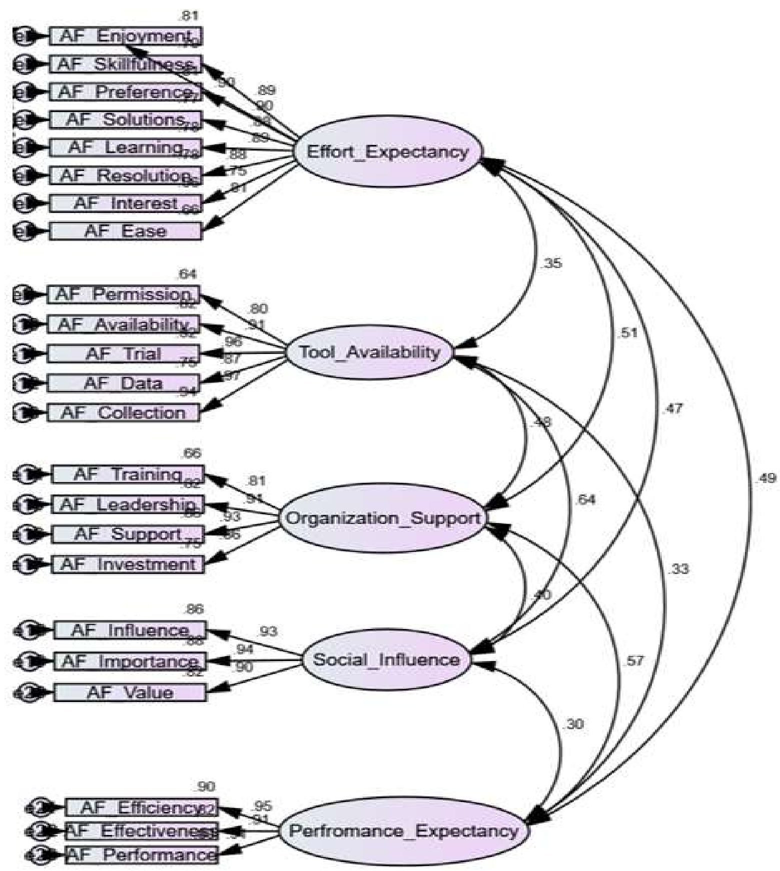

Figure 3: Conceptual Framework for Adoption of HR Analytics in Organizations

This framework illustrates key factors influencing HR analytics adoption, including technological readiness, organizational culture, and data management practices.

Table 4.4: Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
Employe_Performance	<---	Effort_Expectancy	0.198	0.06	3.304	***	par_56
Employe_Performan	<---	Tool_Availability	-0.287	0.061	-	***	par_5

ce					4.739		7
Employe_Performance	<---	Organization_Support	0.285	0.068	4.225	***	par_58
Employe_Performance	<---	Social_Influence	-0.219	0.05	-4.39	***	par_59
Employe_Performance	<---	Perfromance_Expectancy	0.503	0.06	8.376	***	par_60

Interpretation: The structural equation modelling (SEM) regression table indicates that Effort Expectancy (Estimate = 0.198, P < 0.001) and Organization Support (Estimate = 0.285, P < 0.001) have a positive impact on Employee Performance. This suggests that higher levels of effort expectation and robust organizational support lead to improved Employee performance. The variable Performance Expectancy exhibits a positive impact (Estimate = 0.503, P < 0.001), indicating that having higher expectations of performance greatly enhances Employee performance. On the other hand, Tool Availability (Estimate = -0.287, P < 0.001) and Social Influence (Estimate = -0.219, P < 0.001) have a negative impact on Employee Performance. This means that having more tools available and experiencing higher social influence are linked to lower performance. All of these associations have statistical significance.

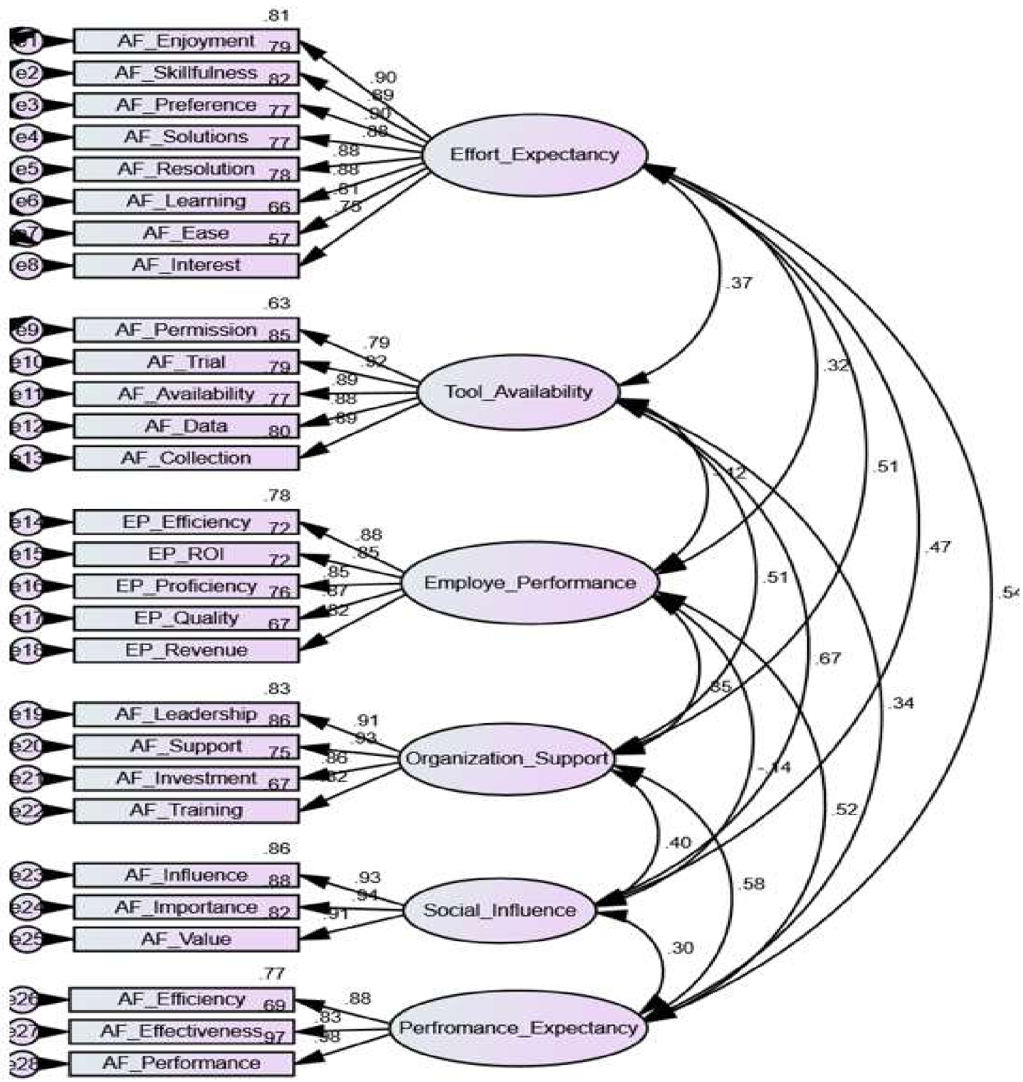

Figure 4: Conceptual Framework of HR Analytics Adoption and Its Impact on Employee Performance

Figure 4 illustrates the conceptual framework linking HR analytics adoption to employee performance. It explores how the implementation of HR analytics tools influences various performance metrics, enabling data-driven decisions and enhancing overall employee effectiveness.

4. CONCLUSION AND RECOMMENDATIONS

The analysis of HR analytics utilization across various sectors in India highlights significant insights into the factors influencing its adoption and effectiveness. The study reveals distinct patterns in how different sectors interact with HR analytics, shaped by variables such as Effort Expectancy, Tool Availability, Organization Support, Social Influence, and Performance Expectancy. In the IT and Financial sectors, analytics tools are most effectively integrated due to low Effort Expectancy and high Tool Availability. These sectors benefit from strong organizational support and are highly influenced by industry standards and peer practices, leading to high adoption rates. Conversely, the Manufacturing sector faces challenges due to higher Effort Expectancy and limited Tool Availability. This sector's traditional practices and resource constraints hinder the adoption and effective use of analytics. The Retail sector shows moderate adoption influenced by company size and tech adoption, with variable support and tool availability. Descriptive statistics indicate that while HR analytics tools are available, their utilization and perceived efficacy vary. Employee performance indicators, such as quality and efficiency, are positively influenced by HR analytics, suggesting that while some areas show benefits, others need improvement. Correlation analysis underscores the complexity of relationships between HR analytics and performance metrics. For instance, Employee Performance shows a positive relationship with Effort Expectancy and Organizational Support but a negative relationship with Tool Availability and Social influence.

5. RECOMMENDATIONS

Following recommendations are being made basis the findings of the study:

1.Tailored Training and Support: Organizations should offer customized training to meet sector-specific needs. For complex sectors like Manufacturing, extensive training is crucial.

2.Enhance Tool Availability: Improve access to advanced analytics tools in resource-limited sectors, possibly through cost-effective solutions or phased upgrades.

3. Strengthen Organizational Support: Cultivate a supportive culture where leadership promotes data-driven practices and provides necessary resources.

4. Leverage Performance Expectancy: Highlight the benefits of HR analytics to drive adoption by linking it to performance improvements.

5. Address Social Influence: Understand and manage peer expectations to align analytics practices with industry standards.

6. LIMITATIONS

The sector-specific study on HR Analytics in India faces several limitations. The variation in data quality and availability across sectors can affect analysis accuracy, leading to biases or gaps. Differences in HR practices and analytics maturity levels can distort comparative results, making generalization difficult. The diversity of industries, each with unique challenges, might not be fully addressed. Rapidly changing HR technology could render findings obsolete. Additionally, organizational confidentiality and reluctance to disclose sensitive HR data can restrict the depth and scope of the study.

7. FUTURE RESEARCH

Future research on HR Analytics in India should focus on several key areas to enhance its impact. Firstly, integrating AI and machine learning in predictive analytics for talent management and employee performance can offer precise forecasting and deeper insights. Studies on the effectiveness of sector-specific HR analytics tools can identify areas for improvement and best practices. Examining HR analytics' impact on employee satisfaction and retention across industries can provide strategic insights. Additionally, exploring HR analytics' role in promoting diversity and inclusion can support equitable practices. Lastly, assessing HR analytics' viability and adaptability in SMEs can reveal challenges and opportunities, aiding customization for India's diverse job market.

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