PERCEPTIONS AND REALITIES OF HR ANALYTICS AND AI: EVIDENCE FROM FIRMS IN LUDHIANA DISTRICT

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Abstract

Purpose: *In the contemporary business landscape, human resource management is seeing a shift. This shift is due to the integration of Analytics and Artificial Intelligence. While many studies talk about the theoretical significance of AI and Analytics in industries, the aims of this study are to understand the levels of awareness, impact, and challenges faced in the implementation of HR analytics and AI among firms of Ludhiana. It seeks to uncover the extent to which HR professionals recognise and utilise these technologies.*

Methods: *An exploratory quantitative research design was utilised. The primary data for study was collected through a structured online questionnaire from 50 professionals of HR of distinct firms across the Ludhiana district. Non-parametric tests such as Friedman's ANOVA, Spearman's correlation, and Kruskal-Wallis were used. Correlation and regression analysis were applied to test the hypotheses.*

Findings: *The awareness levels of HR analytics and AI among HRs were significantly higher than neutral. Training sessions were found to significantly influence awareness of AI. On the other hand, organisational factors other than training sessions had negligible effects. The impact of analytics and AI in recruitment, training development, and performance appraisal was statistically significant. The correlation tests confirmed that higher awareness levels lead to higher positive perceptions of impacts. Lack of tech skills, HR analytical expertise, financial limitations, and resistance to change emerged as major challenges, while partnership and collaboration issues were the most significant differentiators.*

Implications: *Organisations must focus on upskilling, tech investments, ethical governance, and collaborations.*

Originality: *It highlights that awareness alone is not enough, and organisations must address capability, investment, and change-management barriers to translate AI and analytics into real HR value. Therefore, it studies perceptions and realities in actuality.*

Keywords: analytics, artificial intelligence, human resource management

1. INTRODUCTION

1.1 Background

The functions of human resources have undergone a paradigm shift. HR was once regarded as a support function focused on recruitment, payroll, and employee relations. HR has emerged as a strategic partner driving the growth and transformation of organisations. This shift has been propelled by the convergence of two powerful forces – Analytics and Artificial Intelligence (AI). Together, they are changing the definitions of how organisations attract, engage, develop, and retain talent. The amalgamation of data-driven insights and intelligent technologies into HR operations marks the onset of a new epoch, where decisions are not just taken by experience and intuition but are reinforced by evidence and predictive power.

The concept of HR analytics refers to the systematic process of gathering, analysing, and interpretating employee data to enhance decision-making. It enables HR professionals to reveal trends, measure performance, and identify problem areas. By harnessing the power of analytics, organisations take informed decisions about recruitment, employee engagement, training effectiveness, and attrition rates. It makes HR into a proactive, evidence-based function capable of forecasting challenges and designing interventions before they explode.

Simultaneously, artificial intelligence has introduced automation and intelligence into HR processes. According to John McCarthy, "Artificial Intelligence is the science and engineering of making intelligent machines, especially intelligent computer programs.". From AI powered recruitment tools that digitally screen resumes and predict candidate success and culture fit, to chatbots that manage employee queries and digital assistants that support onboarding. Predictive algorithms are now being employed to foretell workforce needs, identify high-potential employees, and even understand employee sentiment through natural language processing. AI in HR improves both efficiency and ensures consistency, reduces bias, and improves employee experience.

The transformation of HR through AI and Analytics is not just technological improvement but indicative of a fundamental change occurring in mindsets. Organisations are moving away from transactional HR models and adopting strategic, data-enabled ecosystems. HR leaders are required to combine human empathy with analytical acumen, blend emotional intelligence with evidence and data-driven insights. This transformation empowers HR departments to implement a policy of aligning people strategies with business goals. It ensures that every talent decision contributes to organisational success.

The significance of this new wave is amplified by the increasing complexity of modern workplaces. Newer challenges, such as globalisation, hybrid work models, skill shortage, and workplace diversity, have made HR decision-making tougher than ever. Solely relying on intuition is unacceptable in current business landscape. AI and analytics provide clarity amid complexity. It helps HR professionals to understand workforce dynamics in real time and craft targeted interventions. Predictive analytics can flag labour who are plausible to leave, enabling HR to take timely retention actions. Similarly, AI-based learning platforms offer personalised employee training and development, ensuring continuous growth and engagement.

1.2 Research Problem

It is historically understood that any transformation is not without its challenges. So is true for HR Analytics and AI. The growing dependence on data raises concerns about ethics, privacy, security, and algorithmic biases. There is also the perceived threat of AI or technology in general replacing human touch among employees. Therefore, the future of HR transformation most probably lies in balance – combining technology with the wisdom of human judgement. The most future-ready organisations are those that use AI and Analytics as enablers of empathy, fairness, and inclusivity. The successful organisations view HR as technology enablers and change agents.

However, not much is known about the perceptions and ground realities of how Analytics and AI affect Human Resource Management and the work of HR professionals. Available literature on the subject has not succeeded in completely capturing the Indian corporate HR conditions, particularly in smaller manufacturing and business zones. A serious research gap lies in the knowledge of how MSMEs perceive HR Analytics and AI and its impact in relatively smaller industrial and corporate hubs such as Ludhiana. Not much is known about their perceptions and realities when it comes to HR Analytics and AI.

1.3 Significance of the Study

Transforming HR with Analytics and AI is not just a trend but a sine qua non in the digital age. It equips HR professionals with tools and technologies to make faster, fairer, impactful, and forward-looking decisions. The true power of this transformation lies in its ability to blend data's precision with human insights. As businesses continue to evolve, HR's role will expand exponentially – from managing talent to shaping the future of work itself. Embracing AI and Analytics will empower HR to move from back offices to the boardrooms.

To gain meaningful insights into the state of transformation, this study conducts a primary research survey among HR professionals across diverse sectors of Ludhiana, Punjab. The aim of the survey was to capture their opinions, readiness, and apprehensions toward adopting AI and Analytical tools within the HR ecosystem.

This study puts the current scenario of Analytics and AI understanding and implementation for firms of Ludhiana under the spotlight, which has not been explored before. Both the renowned business giants and MSMEs are the future of India's economic progress, and Ludhiana's MSMEs and big manufacturing firms have a major role to play in this growth story. Therefore, this study reveals the readiness of HR to face the wave of transformation headed towards Ludhiana's industrial blocks.

1.4 Objectives

1. To determine the awareness levels about HR analytics and AI among firms in Ludhiana
2. To evaluate the impact analytics and AI have in recruitment, training, performance measurement, and employee's retention.
3. To assess the hurdles faced by firms while implementing HR analytics and AI.

1.5 Research Questions and Hypotheses

RQ1: What is current level of awareness of HR analytics and AI among firms in Ludhiana?
RQ2: What is the impact of analytics and AI on HR processes?
RQ3: What are the major challenges in adopting HR analytics and AI among firms in Ludhiana?
Hypotheses formulated for the research were as follows: -

Awareness Levels of HR analytics and AI

H_{01}: Awareness towards HR analytics and AI is neutral among firms in Ludhiana (μ=3).
H_{11}: The awareness towards HR analytics and AI is greater than neutral among firms in Ludhiana ($\mu > 3$).
H_{02}: The organisational factors (firm sector, firm size, respondent position, work experience, or training sessions) do not significantly influence awareness levels towards HR Analytics and AI.
H_{12}: Organisational factors (sector of the firm, firm size, respondent position, work experience, or training sessions) significantly influence awareness levels towards HR Analytics and AI.

Impact of HR analytics and AI

H_{03}: Impact of HR analytics and AI is neutral among firms in Ludhiana (μ=3).
H_{13}: Impact of HR analytics and AI is greater than neutral among firms in Ludhiana ($\mu > 3$).
H_{04}: The median scores of the three impact variables under study do not differ significantly.
H_{14}: The median scores of the three impact variables under study differ significantly.
H_{05}: No correlation exists between awareness towards HR Analytics and AI and its perceived positive impacts.
H_{15}: A significant correlation exists between awareness towards HR Analytics and AI and its perceived positive impacts.

Challenges and Barriers to Implementation

H_{06}: No significant differences among respondents' perceptions of key barriers.
H_{16}: Significant differences among respondents' perceptions of key barriers.

2. REVIEW OF LITERATURE

2.1 Theoretical Review

Angrave et al. (2016) critically examined the widespread optimism surrounding HR analytics and its perceived potential to transform HR. It contended that such expectation is overstated and without proper and in-depth analysis, HR is unlikely to achieve meaningful transformation. The study found that current practices in HR analytics lacked strategic depth. The findings cautioned that ineffective implementation could marginalise HR from strategic decision making and even harm employee interests.

Marler and Boudreau (2017) carried out a review of 14 articles out of 60 identified ones. The findings suggest that adoption remains low despite the evidence that HR analytics improves performance. The academic research is still limited. The research identified a paradox-high potential and proven benefits, yet slow implementation.

Upadhyay and Khandelwal (2018) explored the applications and implications of using AI in hiring. By synthesizing insights from reports, research papers, and industry literature, it highlighted how AI has transformed the recruitment process and improved efficiency for both employees and candidates. The review showed that AI-driven recruitment enables automation, enhances decision-making, and generates value for clients in the recruitment industry. The paper also extended practical recommendations for integrating AI into recruitment workflows.

Giermindl et al. (2021) analysed the emerging role of AI within people analytics and its impact on HR practices such as recruitment, performance measurement, development of personnel, and employee retention. The study highlighted risks, challenges, and ethical implications of applying efficiency-driven analytics to manage humans. Six key perils related to people analytics were discussed. The paper examined the underlying assumptions behind people analytics and gave thought to future technological advancements.

Sharma et al. (2021) provided an overview of HR analytics by studying 144 articles, including 62 peer-reviewed studies using major databases with keywords related to HR and workforce analytics. The research indicated that HR analytics is still an emerging field that supports but does not replace HR practitioners in making decisions. The findings brought to light the limited empirical evidence on analytics in HR. It underlined the need for a universal definition.

Margherita (2022) conducted a literature review to classify and conceptualise crucial themes about HR analytics, addressing gaps in prior research. It identified 106 major topics grouped into 3 categories: enablers of HR analytics, applications, and value. The research underlined the growing integration of AI and cognitive technologies, suggesting an "exponential" evolution of HR analytics.

Nyathani (2023) examined the role of AI in performance evaluation within HR in the digital era. It analysed how AI shifted performance metrics from rigid standards to dynamic indicators. These provided real time feedback and promoted bias free assessments. It explored analytics driven by AI for creating tailored development plans. Ethical concerns and privacy considerations associated with the implementation of AI and big data were also addressed.

Rodgers et al. (2023) explored ethical dimensions in decision making within algorithmic human resource management. They explained how perceptions, judgements, and information use influence ethical strategy selection in AI-driven HR processes using Throughput model framework. The study understood how ethical positions shape AI adoption in HRM. The role of intelligibility and accountability in AI powered HR decisions were brought to light.

John and Hajam (2024) investigated the application of predictive analytics in HRM. The aim of it is to enhance employee's engagement and optimise manpower planning. They reviewed literature, industrial reports, and case studies and assessed the application of analytics within recruitment, employee retention, and alignment of workforce. The study indicated that predictive analytics helped in identifying employees at risk, personalise strategies for engagement, forecast needs of workforce, and improve recruitment related outcomes. The research emphasized the challenges, such as data quality, ethical concerns, and implementation costs.

Raj et al. (2024) reviewed previous research on the evolution of HR analytic in the broader context of tech progress, such as AI, robotics, big data, and business intelligence. They explained how analytics and complex algorithms have transformed workforce management and decision-making processes. The research traced the progression of analytical tools and their adoption in HR practices. The study highlighted how technology has shifted HR from people-driven to data-driven approaches.

Wang et al. (2024) examined implementation of HR analytics. They studied 89 peer reviewed papers from the past 20 years. It aimed to bring to light the determinants of successful HR analytics in organisations. The research proposed a dynamic framework to guide both HR professionals and scholars in implementing HR analytics effectively. The findings offer practical and theoretical insights into factors influencing adoption, including tech, skills, and organisational support.

Cavescu and Popescu (2025) studied the use of AI in HRM, emphasizing recruitment, employee retention, and performance optimisation. Using the PRISMA protocol, they analysed machine learning algorithms for predicting attrition and talent management. They suggested that AI can automate HR processes. It can reduce human bias, and enhance personalisation. Nonetheless, challenges such as privacy of data, resistance to adoption, and biased algorithms persisted. The study brought out the need for ethical AI frameworks.

2.2 Empirical Review

McCartney and Fu (2022) examined the impact of analytics in HR on organisational performance. It was done by analysing data from 155 Irish organisations. They indicated that access to HR tech facilitated analytics in HR, which supported EBM practices and inevitably enhanced organisational performance. The study provided insights into the mechanisms through which HR analytics improves performance and established HR technology as a key antecedent.

Prejith and Kumar (2022) examined the impact of HR analytics on training practices within the IT sector in Kerela. Using a quantitative approach and data collected from 213 HR professionals and IT employees, the findings revealed that HR analytics had a direct positive effect on performance of employees by improving training and development. The research underscored how data-driven HR practices can support continuous learning and employee retention.

Horodyski (2023) investigated the perceptions of job applicants towards recruitment processes. It examined how candidates viewed the utility and easiness in AI tools for hiring. It highlighted that applicants perceived AI positively due to faster response times. Simultaneously, concerns related to the lack in human judgement, low accuracy, and technological immaturity were also raised.

Alabdali et al. (2024) examined the use of algorithm driven human resource management for strategic decision making in firms' HR activities. A scale was developed to measure the use of algorithm based HRM, and data were collected from 234 participants. Upon analysis using PLS SEM, they revealed that algorithm driven HRM significantly impact strategic HR decisions and contributed to competitive advantage. While HR digital maturity was not a significant moderator, strategic HR decision making acted as a mediator.

Ekhande and Khanuja (2024) examined the incorporation of AI and predictive analytics within HRIS for enhancing employee’s engagement. They proposed a comprehensive approach for optimising workforce engagement and retention. The study highlighted the value of multifaceted data integration, system architecture, and ethics. It demonstrated the value of AI and predictive analytics to improve HR decision making and employee experiences.

Kalluri et al. (2024) examined how Tata Consultancy Services implemented AI across HR functions like recruitment, training, workforce analytics, etc. They used both qualitative and quantitative data. They analysed the effects of AI tools on efficiency, operational costs, and employee satisfaction. The study revealed that AI improved HR performance and decision-making. The findings also identified challenges in managing technological transitions and the alignment of AI with human-centric values.

Nayem and Uddin (2024) investigated unbiased AI approach to predict employee's performance by taking into consideration social, physical, and economic factors. The study was based on the data from 1109 employees in a Bangladeshi for-profit organisation. Multiple machine learning models were tested to estimate performance outcomes. These were compared on precision, accuracy, F1-score, and speed to identify the most effective approach. The findings highlighted that AI algorithms could provide just and fair performance evaluations, assisting in ethical HR decisions.

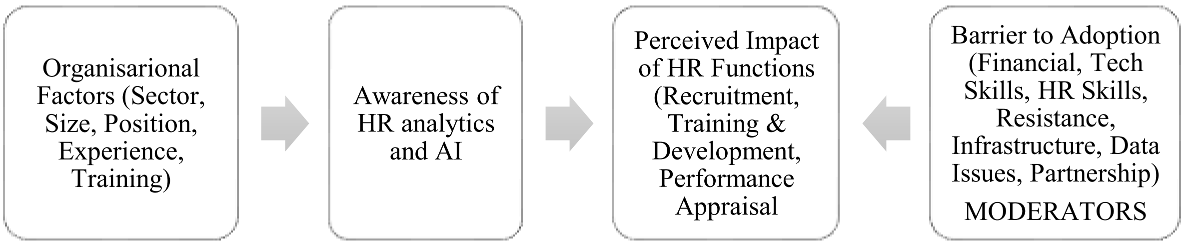
Moon (2025) investigated the impact of AI on HRM in IT sector of India using a mixed method approach. It relied on data collected from 420 employees across 28 states. It revealed that AI influenced employee's retention, employee's engagement, and their decision making. The research looked at technologies such as personalised learning, chatbots, predictive analytics, and virtual reality play a positive role in improving HR outputs. It reveals strong correlations between adoption of AI and effective HR functions.

Sharma and Gupta (2025) examined how AI technologies impacted HR functions within IT firms in India. They used a mixed-methods approach. It combined survey responses from 320 HR professionals with 25 qualitative interviews. The analysis showed that AI adoption improved the efficiency of recruitment, minimised bias, and supported data-driven decision-making. The research found that firm having greater AI maturity achieved better integration between analytics and manpower planning. But it also raised concerns regarding reduced human interaction and privacy risks.

2.3 Conceptual Framework

The present study conceptualises the relationship between organisational factors (firm size, firm sector, HR professionals' work experience, HR professionals' job position, and training sessions), awareness levels, perceived impact, and barriers related with HR analytics and AI integration among firms in Ludhiana. Existing literature suggests that organisational features shape the awareness of HR Analytics and AI, which in turn influence the perceived impacts across HR dimensions. Prior research underlines the multiple challenges that moderate the adoption and use of HR technologies. Accordingly, the conceptual model places organisational factors as predictors of awareness, awareness as an antecedent of perceived impact, and barriers as moderating factors. This framework is in support of the present study's objectives and hypotheses.

Figure 1: Conceptual Framework



3. METHODOLOGY

3.1 Research Design

Exploratory research was conducted to investigate the research questions. It provided understanding into the current condition of analytics and AI transformation in Ludhiana. It was considered suitable due to the limited availability of past data, with only a few studies available for reference. The study used a quantitative research design.

3.2 Sampling Design

The population/universe of the study consists of the firms of Ludhiana. The sample size for this study was limited to 50 firms. The convenience sampling technique was used for drawing the sample.

3.3 Data Collection Methods

The survey method was adopted to collect the primary data. An online questionnaire was administered to the respondents to gather the required information. The respondents were contacted through online communication channels and were requested to voluntarily participate in the survey. The data was gathered digitally.

3.4 Research Instruments and Measurements

The research used a structured online questionnaire. It was administered using Google Forms with 5-point Likert scale items for attitudinal variables, dichotomous, and multiple-choice questions. Nominal scales were used for organisational profile variables. Variables under study included independent variables (Organisational factors) and dependent variables (Awareness, Impact, Barriers). All constructs were quantifiable for statistical testing.

3.5 Data Analysis Methods

MS Excel was used for coding the responses. Descriptive statistics, One sample t test, One Way ANOVA/Kruskal-Wallis, Linear Regression, Repeated Measure/Friedman's ANOVA (Non-parametric), and Spearman's Correlation Matrix have been used for hypothesis testing and interpretation of the results. Jamovi software was utilised to perform the statistical analysis.

3.6 Reliability and Normality Testing

Cronbach's Alpha and Shapiro Wilk tests were used to check reliability and normality. Cronbach's α scale reliability test was conducted. The results are illustrated below.

Table 1: Cronbach's Alpha Reliability Test

Cronbach's α
0.791

Reliability, as measured by Cronbach's α is 0.791; it indicates good internal consistency among all the items. This shows that the items collectively measure the underlying construct with acceptable reliability because values above 0.7 are considered satisfactory in social sciences research.

The above result means that the scale used for data collection successfully measures the variables that are part of the study. Shapiro Wilk test determined the normality of data. The results for Shapiro Wilk Normality test are tabulated below.

Table 2: Shapiro Wilk Normality Test

		Shapiro Wilk	
	N	**W**	**p**
Firm sector	50	0.820	<.001
Firm size	50	0.768	<.001
Respondent position	50	0.530	<.001
Work experience	50	0.827	<.001
Aware HR analytics	50	0.815	<.001
Aware HR AI	50	0.872	<.001
Training sessions	50	0.637	<.001
Use use not	50	0.634	<.001
Adoption levels	50	0.879	<.001
Impact recruitment	50	0.874	<.001
Impact t&d	50	0.810	<.001
Impact performance app	50	0.868	<.001
Barrier finance	50	0.897	<.001
Barrier tech skills	50	0.870	<.001
Barrier resistance	50	0.859	<.001
Resistance source	50	0.627	<.001
Barrier infrastructure	50	0.831	<.001
Barrier data	50	0.868	<.001
Barrier HR skills	50	0.821	<.001
Barrier partnership	50	0.883	<.001
Perception necessary	50	0.380	<.001
Perception strategic role	50	0.255	<.001
Perception replacement HR roles	50	0.467	<.001
Concern data security	50	0.467	<.001
Concern bias	50	0.622	<.001
Perception replace humans	50	0.627	<.001

For all the listed variables in the above table, the p-values are <.001, and the W-values are all well below 1. It implies that all variables significantly deviate from a normal distribution. The data is found to be non-normal. Because of non-normality, non-parametric statistical techniques were more appropriate for further analysis.

4. RESULTS

4.1 Demographic Profile

Table 3: Sector of the Respondent Firms

Sector of the Firm	Count	Percentage
Other	18	36.0%
Engineering/Manufacturing	17	34.0%
Bicycles	7	14.0%
Textile/Hosiery	4	8.0%
Auto Components	4	8.0%

Manufacturing/Engineering sector leads the sample after the cumulative of ‘Others’ with 34%, followed by bicycles with 14%, and textiles/hosiery and auto parts with 8% each.

Table 4: Size of the Respondent Firm (in number of employees)

Size of the Firm (Employees)	Count	Percentage
Less than 50	19	38.0%
51–250	14	28.0%
251–1000	7	14.0%
Above 1000	10	20.0%

38% of the sample is made up of firms with less than 50 employees, followed by 28% with 51-250 employees. There are 10 big firms with over 1000 employees.

Table 5: Job Position of the Respondent

Respondent's Position	Count	Percentage
HR Manager	22	44.0%
Other	16	32.0%
HR Executive	12	24.0%

44% of the respondents were HR managers, while 24% held the position of HR Executives.

Table 6: Work Experience of the Respondent

Work Experience	Count	Percentage
1–3 years	26	52.0%
Less than 1 year	9	18.0%
More than 6 years	8	16.0%
4–6 years	7	14.0%

52% of the respondents have 1-3 years of work experience, while 18% have experience of less than a year. Only 14% have work experience of 4-6 years.

4.2 Descriptive Statistics

Table 7: Descriptive Statistics for Awareness Variables

	Aware HR analytics	Aware HR AI	Training sessions
N	50	50	50
Mean	3.76	3.74	0.500
Median	4.00	4.00	0.500
standard deviation	1.02	0.944	0.505

The above table indicates that the respondents tend to have a good awareness of HR analytics and HR artificial intelligence, with only moderate variability in their responses. Training sessions are equally distributed among participants, implying that not all have received formal training in these areas. Only 50% of the respondents are affirmative of having received any formal training in the past year.

Table 8: Descriptive Statistics for Impact Variables

Descriptives – Impact			
	Impact recruitment	Impact t&d	Impact performance app
N	50	50	50
Mean	3.50	3.58	3.54
Median	4.00	4.00	4.00
standard deviation	0.931	0.883	0.930

The above results show that respondents perceive a positive impact of analytics and AI applications amongst all three HR functions – recruitment, training development, and performance appraisal. The mean scores are close to 4 on a 5-point scale. It suggests a generally favourable perception, while a moderate standard deviation implies that most participants agree with some variations in the degree of perceived impact.

Table 9: Descriptive Statistics for Barrier Variables

Descriptives – Barriers	N	Missing	Mean	Median	SD
Barrier finance	50	0	3.46	3.50	0.994
Barrier tech skills	50	0	3.58	4.00	0.950
Barrier resistance	50	0	3.44	3.50	0.884
Barrier infrastructure	50	0	3.28	3.50	0.904
Barrier data	50	0	3.38	3.00	0.830
Barrier HR skills	50	0	3.50	4.00	0.863
Barrier partnership	50	0	3.00	3.00	0.969

The above table provides descriptive statistics for various barriers faced to implement analytics and AI, with no missing data for any variable. The barriers considered include financial constraints, technical skills, resistance to change, infrastructure, data-related issues, HR skills, and partnership challenges. Overall, the findings suggest that lack of technical skills, lack of HR analytical skills, and financial constraints are among the most significant barriers to adopt and implement of HR analytics and AI. It is reflected through their higher mean scores. On the other hand, partnership and infrastructure-related issues are seen as lesser barriers. A moderate standard deviation is observed across all variables, which highlights some variations in perceptions, possibly due to differences in organisational readiness and exposure to technologies.

4.3 Inferential Statistics

One Sample t test was determined whether the mean awareness levels of HR analytics and HR AI differed significantly from the test value of 3, which represented neutral point on the measurement.

Table 10: One Sample t test for Awareness Variables

		Statistic	df	p
Aware HR analytics	student's t	5.26	49.0	<.001
Aware HR AI	student's t	5.55	49.0	<.001
Note. H_a $\mu > 3$				

Since both p-values are less than 0.001, the results are statistically significant. It indicates that the mean awareness for both HR Analytics and HR AI is significantly different from 3. Given the mean values of 3.76 (HR Analytics) and 3.74 (HR AI), it can be inferred that the respondents demonstrate a significantly higher-than-neutral levels of awareness towards HR Analytics and HR AI.

Linear regression was calculated to ascertain whether organisational factors such as firm sector, firm size, respondent position, work experience, or training sessions significantly influenced the awareness levels of HR Analytics and HR AI.

Table 11: Linear Regression-HR Analytics Awareness and Organisational Factors

Fit Measures

Model	R	R^2
1	0.248	0.0617

Model coefficients – aware HR analytics

Predictor	estimate	SE	t	p
Intercept	2.4212	0.836	2.897	0.006
Firm sector	0.0952	0.121	0.787	0.435
Firm size	0.1761	0.177	0.993	0.326
Respondent position	0.3968	0.354	1.120	0.269
Work experience	0.0311	0.165	0.188	0.852
Training sessions	0.1663	0.307	0.542	0.591

The above results show R=0.248, which indicates a weak positive correlation between the independent variables (firm sector, firm size, respondent position, work experience, and training session) and the dependent variable (awareness towards HR Analytics). The low $R^2 = 0.0617$ confirms that predictors collectively explain only small portion of the variations in awareness. The regression results reveal that organisational factors have a statistically significant influence on awareness of HR Analytics.

Another model was developed by taking awareness towards HR AI as a model coefficient. It is elucidated as follows:

Table 12: Linear Regression-HR AI and Organisational Factors

Fit Measures

Model	R	R^2
1	0.439	0.193

Model coefficients – aware HRAI

Predictor	Estimate	SE	t	p
Intercept	3.3143	0.716	4.628	<.001
Firm sector	-0.0162	0.104	-0.157	0.876
Firm size	0.1441	0.152	0.948	0.348
Respondent position	0.0687	0.304	0.226	0.822
Work experience	-0.0935	0.141	-0.661	0.512
Training sessions	0.6819	0.263	2.592	0.013

It can be inferred from the above table that only training sessions is a significant predictor of awareness towards HR artificial intelligence. Other organisational factors (firm sector, firm size, respondent position, work experience) show no significant effects. The above model has modest explanatory power, i.e., $R^2 = 0.193$.

One sample t test determined if the mean ratings for different HR dimensions – recruitment, training and development, and performance appraisal – significantly differ from the neutral midpoint of 3 on a 5-point Likert scale.

Table 13: One Sample t test for Impact Variables

		Statistic	df	p
Impact recruitment	student's t	3.80	49.0	<.001
Impact t&d	student's t	4.65	49.0	<.001
Impact performance app	student's t	4.10	49.0	<.001
Note: H_a is $\mu > 3$				

Since all p-values are <0.001, the results are statistically significant. This concludes that all three dimensions-recruitment, training and development, and performance appraisal – the average impact ratings are notably greater than the neutral midpoint (3). Therefore, the respondents agree that the HR practices have a positive and meaningful impact on these dimensions of HR.

The Friedman test examined if there are significant differences in the median scores of the three related variables discussed in the above t-tests.

Table 14: Friedman Test for Impact Variables

Friedman

χ^2	df	p
1.18	2	0.554

The Friedman test results ($\chi^2 = 1.18$, p = 0.554) underscore no significant differences in the impact levels of studied variable across three functions – recruitment, training and development, and performance appraisal. This suggests that the respondents perceive the impact to be consistent across all three HR domains. It implies a uniform influence of the factors being measured.

The table below shows the Spearman's rank correlation coefficient (ρ) between awareness and perceived impact variables related to HR Analytics and Artificial Intelligence (HRAI). Spearman's rho is used because it measured strength as well as direction of monotonic relationships among variables on ordinal scales.

Table 15: Correlation Matrix-Awareness and Impact

		Aware HR analytics	Aware HR AI	Impact recruitment	Impact t&d	Impact performance app
Aware HR analytics	Spearman's rho	—				
	df	—				
	p-value	—				
Aware HR AI	Spearman's rho	0.654***	—			
	df	48	—			
	p-value	<.001	—			
Impact recruitment	Spearman's rho	0.473***	0.377**	—		
	df	48	48	—		
	p-value	<.001	0.003	—		
Impact t&d	Spearman's rho	0.350**	0.408**	0.825***	—	
	df	48	48	48	—	
	p-value	0.006	0.002	<.001	—	
Impact performance app	Spearman's rho	0.345**	0.416**	0.798***	0.836***	—
	df	48	48	48	48	—
	p-value	0.007	0.001	<.001	<.001	—
Note: H_a is a positive correlation						
Note: * p < .05, ** p < .01, *** p < .001, one-tailed						

Correlations are positive and statistically significant, indicating that as awareness of HR Analytics and HR AI increases, the perceived positive impacts of these technologies on the above HR functions also increase.

A Repeated Measure ANOVA (Non-parametric) was used to find whether there were significant differences among respondents' perceptions of seven barriers to HR Analytics and HR AI implementation.

Table 16: Friedman and Durbin-Conover for Barrier Variables

Friedman		
χ^2	df	p
23.9	6	<.001

Pairwise Comparisons (Durbin-Conover)				
			Statistic	**p**
Barrier finance	-	Barrier tech skills	1.167	0.244
Barrier finance	-	Barrier resistance	0.252	0.801
Barrier finance	-	Barrier infrastructure	1.009	0.314
Barrier finance	-	Barrier data	0.505	0.614
Barrier finance	-	Barrier HR skills	0.851	0.395
Barrier finance	-	Barrier partnership	3.185	0.002
Barrier tech skills	-	Barrier resistance	0.915	0.361
Barrier tech skills	-	Barrier infrastructure	2.176	0.030
Barrier tech skills	-	Barrier data	1.671	0.096
Barrier tech skills	-	Barrier HR skills	0.315	0.753
Barrier tech skills	-	Barrier partnership	4.352	<.001
Barrier resistance	-	Barrier infrastructure	1.261	0.208
Barrier resistance	-	Barrier data	0.757	0.450

Barrier resistance	-	Barrier HR skills	0.599	0.550
Barrier resistance	-	Barrier partnership	3.437	<.001
Barrier infrastructure	-	Barrier data	0.505	0.614
Barrier infrastructure	-	Barrier HR skills	1.861	0.064
Barrier infrastructure	-	Barrier partnership	2.176	0.030
Barrier data	-	Barrier HR skills	1.356	0.176
Barrier data	-	Barrier partnership	2.681	0.008
Barrier HR skills	-	Barrier partnership	4.037	<.001

The test result, χ^2 (6) = 23.9, p < .001, shows a statistically significant difference among the perceived severity of these barriers. Overall, the Friedman test and post-hoc analysis reveal that respondents recognise several barriers to HR Analytics and HR AI. The issues related to partnerships and collaborations are outliers as the most significant differentiators. These findings suggest that working on improving inter-departmental and cross-functional collaborations could be helpful for successful HR Analytics adoption.

5. DISCUSSION

For the awareness of HR analytics, the t-statistic is 5.26 with 49 df and a p-value <0.001. Similarly, the awareness of HR artificial intelligence, the t-statistic is 5.55 with 49 degrees of freedom and a p-value <0.001. Since p-values are less than 0.001. We reject the H_{01}. Therefore, the awareness towards HR Analytics and AI is greater than neutral among firms in Ludhiana. The linear regression between the independent variables (firm sector, firm size, respondent position, work experience, and training session) and the dependent variable (awareness of HR Analytics) was found to be 0.248, which is very weak. The regression model does not show a significant relationship between the independent and dependent variables. Therefore, the H_{02} is not rejected. The organisational factors do not significantly influence awareness levels towards HR Analytics and AI. Awareness towards HR Analytics and AI is not a function of firm sector, firm size, respondent position, work experience, or training session. The t-statistics for impact on recruitment, impact on training and development, and impact on performance appraisal were found to be 3.80, 4.65, and 4.10, respectively, and p-values were <0.001 for all three variables, with 49 degrees of freedom. It implies rejection of H_{03}. Hence, the impact of HR analytics and HR AI in recruitment, training development, and performance appraisal is greater than neutral among firms in Ludhiana. The Friedman test on impact variables yielded a chi square of 1.18, 2 df, and a p-value of 0.554. This is greater than the significance level (0.05). As a result, H_{04} is not rejected. So, there is no significant difference in the impact levels of the studied impact variables. Spearman's Rank Correlation coefficients between awareness and perceived impact variables related to HR analytics and HR AI were all positive and statistically significant with p-values of <0.05. Therefore, H_{05} is rejected. There exists a correlation between awareness towards HR analytics and AI and its perceived positive impacts. A Repeated Measure/Friedman's ANOVA (Non-Parametric) examined whether there were significant differences among respondents' perceptions of the seven key barriers to HR Analytics and AI implementation. The chi-square value was 23.9 with p-value <0.001. This leads to rejection of H_{06}. There are significant differences among respondents' perceptions of key barriers. The barrier due to the lack of partnerships consistently shows significant differences with most other barriers (financial constraints, lack of tech skills, resistance, infrastructure, unreliable data, and lack of HR skills).

6. CONCLUSION

The study examined awareness, impact, and barriers associated with the adoption of HR analytics and AI among firms of Ludhiana. It revealed that awareness levels of HR analytics and AI among professionals of HR are significantly higher than neutral. It reflects a growing recognition of data-driven HR practices in the region. However, the regression analysis showed that organisational or individual factors like firm size, sector, and work experience of HR professionals do not significantly influence awareness levels. Therefore, we can conclude that awareness is more individualistic and exposure-based rather than structural. Training sessions in the past year emerged as the only variable that predicted awareness towards AI in HR, underlining the significance of learning and upskilling initiatives.

The study found that HR analytics and AI have a significant impact on recruitment, training development, and appraisal of performance. The respondents believe these technologies to be enhancers of efficiency, objectivity, and decision-making quality across HR dimensions. A uniformity of the impact across the three areas signals a comprehensive potential of Analytics and AI in HRM. The positive and significant correlation between awareness and perceived impact indicates that as employees become more knowledgeable, they are more capable to appreciate the importance of analytical and AI technologies for strategic HR purposes.

In assessing the barriers, the research identified several barriers and challenges. However, lack of technical skills and HR skills, financial constraints, and resistance to change were highlighted as major challenges. The Friedman test revealed significant differences among respondents' perceptions of these barriers. The partnership and collaboration issues stood out as the most distinctive. These findings underscore the fact that implementation remains hindered by capability and structural gaps.

Overall, the research confirmed that HR professionals in Ludhiana exhibit awareness and a positive perception of AI and Analytics in HR. Nevertheless, they face practical hurdles in adoption. The study brought to light that successful integration of technologies in HR requires not only technological readiness but also human adaptability, skill development, and cross-functional collaborations. As firms transition toward evidence-based HR, aligning technology with empathy and ethics will define the future of sustainable HR. The findings advocate a balanced approach, wherein human wisdom blends with algorithmic precision.

6.1 Implications

6.1.1 Theoretical Implications

The study supports technology acceptance and diffusion theories by establishing that awareness is not determined by characteristics of an organisation, but is based on exposure and is learning-driven. Positive correlation between awareness and perceived impact supports the theoretical link between cognitive familiarity and perceived usefulness of advanced HR technologies. The different perception of barriers also extends existing theory by highlighting collaboration and partnership gaps as a separate theoretical construct influencing AI adoption in HR.

6.1.2 Practical Implications

For practitioners, the results suggest that organisations should prioritise training and development through upskilling rather than depending on structural attributes to enhance HR Analytics and AI awareness. HR leaders should deploy Analytics and AI across HR functions as their impacts are uniformly positive. Policymakers and top management must invest in cross-functional partnerships to improve technical and HR capabilities. Managers must address resistance to change to enable effective adoption and acceptance of the newer technologies. Investment in collaborative ecosystems can significantly reduce adoption barriers.

6.1.3 Social Implications

Increased awareness and positive perceptions of HR Analytics and AI might indicate a shift towards more objective, fair, transparent, and data-driven HR practices. It can imply an enhancement in efficiency and justness of HR decisions like recruitment, selection, performance appraisal, etc. However, identified gaps in skills and partnerships suggest a need for inclusive learning opportunities and institutional support to prevent technological exclusion. It might be suggestive of a need to redesign management and business curriculum in higher education to integrate AI and other technological tools. By aligning AI adoption with human values, ethics, and collaboration, enterprises can promote sustainable employment practices and contribute to responsible technology adoption.

6.2 Recommendations

- Training and Skill Development: Organisations should schedule regular training workshops and certification programs to build analytical and AI skills of HR professionals.
- Integration of HR Analytics: HR Analytics should be integrated into organisational strategy and decision-making. It ensures that decisions are data-driven and HR policies are evidence-based.
- Investment in HR tech Infrastructure: Firms should invest in HR Analytics software, AI tools, and data management systems to improve efficiency.
- Promotion of Data-Driven Culture: Management should encourage data-based decision-making across all HR functions to reduce reliance on intuition.
- Encouraging Cross-Functional Collaborations: Partnerships between HR, IT, and data teams can strengthen and ensure successful AI and analytics adoption.
- Emphasis on Ethical and Responsible AI: Organisations must ensure data privacy, eliminate bias, and promote ethical AI practices in HR.
- Addressing Resistance to Change: Change management initiatives, communication programs, and leadership involvement help to reduce employee apprehension.
- Developing Localised Solutions: MSMEs in Ludhiana should adopt affordable, scalable, and locally relevant AI models to suit their needs.
- Monitor and Evaluate Outcomes: Continuous assessment of AI and Analytics performance should be carried out to track productivity and employee satisfaction.
- Government and Academic Collaborations: Partnerships with academic institutions can provide research funding and training in HR Analytics for local industries. Governments should work on framing educational programs and academic courses that integrate Analytics and AI in theoretical learning at B-schools.

6.3 Limitations

Although this study offers various lessons into awareness, impacts, and barriers of HR analytics and AI among firms of Ludhiana, yet it remains subject to a few limitations. The sample size was limited to 50. It does not represent the wider population of HRs across different sectors. Generalisability in results is restricted due to the use of the convenience sampling technique. Social desirability and selective reporting bias might exist due to the use of a self-reported online questionnaire. Since the present study relied solely on quantitative data, it did not capture deeper contextual explanations and practical realities related to Analytics and AI adoption. The study's analysis was cross-sectional. Therefore, the findings may not hold true in times when HR Analytics and AI are evolving rapidly. Technological adoption and organisational practices may change with time.

6.4 Future Scope

Future researchers can incorporate larger and more diverse sample sizes, including multiple districts, industries, and types of organisations. The future research should consider adopting the mixed-methods approach to better capture lived experiences, cultural frictions, and implementation realities that often go unnoticed in quantitative research designs. Longitudinal designs will allow researchers to track changes and produce more reliable results. Future researchers may also build predictive or structural models for studying causal relationships between variables. Scholars may explore dimensions such as ethical concerns, governance frameworks, the role of leadership, sustainability implications, and the threat to jobs in enabling AI and Analytics-driven HR transformation.

Acknowledgement

We would like to acknowledge and express gratitude all the respondents (HR Managers, HR Executives, and HR staff) from various firms across Ludhiana for their responses and help in data collection.

Authorship contribution

The first author conducted data collection, review of literature, analysis, and interpretation of results. Academic guidance throughout the research process was provided by the second author. Second author contributed to refining the research design, and assisted in reviewing, editing, and improving the overall structure and clarity of the manuscripts.

Funding

No funds were obtained to conduct the research at any stage.

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