Journal DOI: 10.36713/epra1013 | SJIF Impact Factor (2026): 8.748 ISSN: 2347-4378
EPRA International Journal of Economics, Business and Management Studies (EBMS)
Volume: 13 | Issue: 7 | July 2026 -Peer-Reviewed Journal

AN EMPIRICAL STUDY ON THE AWARENESS AND UNDERSTANDING OF HR ANALYTICS TOOLS AMONG HR PROFESSIONALS IN THE DELHI NCR

Chitranshi Singh[1], Dr. Anshu Choudhary[2]

[1]*Research Scholar, NICE School of Business Studies, Shobhit Institute of Engineering and Technology, Deemed to be University, Meerut*

[2]*Associate Professor, NICE School of Business Studies, Shobhit Institute of Engineering and Technology, Deemed to be University, Meerut*

ABSTRACT

The growing reliance on data-driven practices has transformed Human Resource Management (HRM) into a strategic partner in organizational performance. This study investigates the awareness and understanding of HR analytics tools among HR professionals in the Delhi NCR region, with a particular emphasis on the IT and ITES sectors. Employing a descriptive and empirical design, primary data were collected through structured questionnaires and semi-structured interviews with HR managers and executives. The dataset was analyzed using descriptive statistics and inferential tests to evaluate familiarity, application levels, and perceived challenges in adopting HR analytics. Findings reveal that while a majority of respondents demonstrate moderate awareness of advanced tools such as Tableau, Power BI, and SAP SuccessFactors, their practical application remains limited to basic HR functions such as recruitment and performance monitoring. Key barriers include inadequate technical skills, concerns over data privacy, and the persistence of traditional decision-making practices. Conversely, organizations that invested in training and digital infrastructure reported higher adoption rates and improved alignment of HR strategies with business objectives. The study underscores the importance of bridging the knowledge–practice gap through continuous capability-building and fostering a data-driven culture. These insights contribute to both scholarly literature on HR analytics adoption in emerging economies and offer practical guidance for organizations seeking to integrate artificial intelligence and analytics into their HR systems.

KEYWORDS: *HR Analytics; Artificial Intelligence; Human Resource Management; Adoption Barriers; Awareness and Understanding; IT/ITES Sector; Data-Driven HR; Organizational Readiness; Strategic HR Practices; Digital Transformation*

1. INTRODUCTION

The field of Human Resource Management (HRM) has undergone a fundamental transformation over the past two decades. Traditionally, HR was perceived primarily as an administrative and support function, responsible for hiring, payroll, compliance, and employee welfare. However, the contemporary organizational landscape demands much more. With the growing complexity of global business operations, volatile labor markets, and heightened competition for talent, HR has evolved into a strategic partner that directly contributes to business outcomes. At the center of this evolution is the adoption of HR Analytics (HRA), which leverages data-driven techniques to generate actionable insights for talent acquisition, employee development, performance management, and retention. Scholars widely agree that HR analytics provides a mechanism for linking workforce decisions to organizational strategy and financial performance (Carlucci & Schiuma, 2020; McIver & Lengnick-Hall, 2018).

In simple terms, HR analytics refers to the systematic collection, analysis, and interpretation of workforce data to enhance decision-making. By applying statistical models, predictive algorithms, and visualization tools, HR professionals can move from intuition-based decisions to evidence-based practices. This transformation is especially critical in knowledge-intensive sectors such as Information Technology (IT) and Information Technology Enabled Services (ITES), where rapid technological change and high employee mobility create a pressing need for reliable workforce insights (Zeidan & Itani, 2020). The Indian context is particularly relevant here. With Delhi NCR emerging as a key hub for IT/ITES industries, organizations face increasing pressure to adopt analytics tools that can provide agility, competitiveness, and alignment of HR strategy with business outcomes (Shivam, 2022).

Despite this promise, the actual state of HR analytics adoption in India remains uneven. Several industry reports highlight a paradox: while HR leaders frequently acknowledge the importance of analytics, practical implementation lags behind global standards (Shet et al., 2021). Awareness of tools such as Power BI, Tableau, SAP SuccessFactors, or Oracle HCM is growing, but deep understanding of how these tools can be integrated into HR processes is still limited (Jain & Jain, 2019). This gap between awareness (knowing about the tools) and understanding (knowing how to apply them effectively) represents a critical challenge. Research on HR transformation has emphasized that without adequate understanding, awareness alone does not translate into effective usage, thereby creating what scholars term the “knowing–doing gap” (George & Kamalanabhan, 2016).

Globally, the HR analytics market has been growing at a compound annual growth rate (CAGR) exceeding 12%, with projections of continued expansion due to digital transformation and the shift toward data-driven HR (Markets & Markets, 2019). Organizations worldwide are investing in analytics not only to improve efficiency but also to enhance employee experience, optimize recruitment pipelines, and predict attrition risks (Avrahami et al., 2022). In developed economies, HR analytics has become embedded in decision-making frameworks, with HR professionals expected to demonstrate data literacy as part of their core competencies.
In contrast, Indian organizations—especially those in emerging urban hubs like Delhi NCR—are still in the process of mainstreaming HR analytics. While leading multinational corporations have adopted advanced AI-driven tools, smaller firms and domestic companies often face barriers such as inadequate infrastructure, lack of skilled analysts, and resistance from employees who fear a loss of the "human touch" in HR decisions (Rathi, 2018). Additionally, cultural and organizational factors play a role. Studies indicate that hierarchical decision-making, risk aversion, and privacy concerns may limit the extent to which HR managers feel comfortable relying on analytics (Leicht-Deobald et al., 2019). These barriers highlight the importance of contextual studies that investigate the specific factors influencing adoption in India.

The literature identifies several inhibitors to the effective adoption of HR analytics. First, the issue of data quality is recurrent. Inaccurate or incomplete data undermines the credibility of analytics, making managers hesitant to base critical workforce decisions on such insights (Marler & Boudreau, 2017). Second, technical skills represent a bottleneck. Unlike finance or operations professionals, many HR practitioners do not have formal training in statistics, programming, or analytics software, leading to limited confidence in using these tools (Upadhyay & Khandelwal, 2018). Third, ethical and privacy concerns complicate adoption. Collecting and analyzing sensitive employee data can raise questions of surveillance, bias, and fairness, particularly in contexts where regulatory frameworks are still evolving (Leicht-Deobald et al., 2019). Finally, resistance to change persists among both HR professionals and employees, who may perceive analytics as reducing the human element of HR practices or as threatening job security (Ulrich, 2016).

While global literature provides robust insights into HR analytics adoption, the Indian perspective remains under-researched. Few studies systematically examine how HR professionals in Delhi NCR—home to a diverse set of IT/ITES organizations—perceive analytics tools. Moreover, most prior work has focused on either the strategic benefits of analytics or the technical capabilities of tools. Limited attention has been given to the dual dimensions of awareness and understanding, which are prerequisites for effective adoption. This gap is significant because organizations may invest heavily in software without realizing Practically, the findings can guide HR leaders, policymakers, and practitioners in designing interventions that bridge the knowledge–practice gap. For example, targeted training programs, clear communication strategies about data privacy, and investments in digital infrastructure can enhance adoption. The study also provides actionable insights for organizations seeking to integrate HR analytics as part of broader digital transformation initiatives. By understanding both the opportunities and challenges, organizations can better align HR practices with strategic goals, improve employee experiences, and gain a competitive edge in a rapidly evolving market.

2. LITERATURE REVIEW

2.1 Conceptual Foundations of HR Analytics

Human Resource Analytics (HRA) represents the convergence of data science and HRM. The core principle is to harness organizational data to inform and improve workforce-related decisions, moving HR from a reactive to a proactive and predictive role (Marler & Boudreau, 2017). Recent scholarship defines HR analytics as "the systematic identification and quantification of the people drivers of business outcomes" (Zeidan & Itani, 2020). This conceptualization reflects a paradigm shift: HR professionals are no longer only custodians of administrative functions but are expected to deliver measurable value by linking talent management decisions to organizational performance (Carlucci & Schiuma, 2020).

2.2 Global Trends in HR Analytics Adoption

Globally, the HR analytics market is expanding rapidly, with analysts forecasting double-digit growth rates due to increased investment in artificial intelligence (AI) and machine learning applications (Avrahami et al., 2022). Studies in North America and Europe suggest that large organizations have already institutionalized analytics for recruitment, performance appraisal, and retention management (Laumer et al., 2017). In particular, predictive analytics has gained traction for anticipating turnover risks and workforce planning. Moreover, global best practices emphasize embedding analytics into broader business intelligence frameworks, thereby enhancing strategic alignment (McIver & Lengnick-Hall, 2018). However, researchers also caution that adoption is uneven across industries, with knowledge-intensive sectors like IT/ITES leading, while traditional manufacturing lags behind (Shet et al., 2021).

2.3 HR Analytics in Emerging Economies, with a Focus on India

Emerging markets present unique opportunities and challenges for HR analytics. India, with its rapidly digitizing economy and large IT workforce, is increasingly viewed as a fertile ground for analytics adoption (Shivam, 2022). Yet, recent studies highlight that Indian organizations remain in the early stages of maturity. For example, Saxena (2025) observed that while HR leaders in metropolitan hubs such as Delhi NCR express optimism about analytics, they often lack concrete roadmaps for integration. Similarly, Sharma (2025) emphasized that smaller firms encounter structural constraints, including insufficient budgets, outdated systems, and lack of skilled professionals. This reflects a broader pattern in emerging economies where enthusiasm for analytics is tempered by infrastructural and cultural limitations (Rathi, 2018).

2.4 Awareness vs. Understanding: The Knowing–Doing Gap

A recurring theme in literature is the gap between awareness of HR analytics tools and the actual ability to use them effectively. George and Kamalanabhan (2016) described this as the "knowing–doing gap," whereby HR professionals are aware of technological possibilities but are unable to translate knowledge into practice. Recent empirical work reinforces this distinction. For instance, Alam et al. (2025) reported that while 70% of HR professionals in their sample recognized the importance of tools such as Tableau and Power BI, fewer than 30% reported confidence in applying them to solve workforce problems. This finding underscores the importance of moving beyond surface-level awareness to cultivate deep understanding, which includes statistical literacy, data visualization skills, and the ability to interpret results in organizational contexts.

2.5 Barriers to Adoption: Technical, Ethical, and Cultural Dimensions

The literature identifies several categories of barriers.

i. Technical barriers include poor data quality, lack of integration across HR systems, and absence of robust IT infrastructure (Marler & Boudreau, 2017).
ii. Skill-related barriers stem from the limited analytical literacy of HR professionals, who often lack formal training in data analysis or software applications (Upadhyay & Khandelwal, 2018).
iii. Ethical barriers revolve around concerns of privacy, surveillance, and algorithmic bias (Leicht-Deobald et al., 2019). Scholars caution that analytics systems, if poorly designed, may reproduce biases embedded in historical data, leading to discriminatory outcomes.
iv. Cultural barriers in contexts such as India include hierarchical structures, resistance to automation, and skepticism regarding the replacement of human judgment with algorithmic decision-making (Ulrich, 2016).

These challenges collectively create resistance, slowing down the adoption curve despite demonstrated benefits.

2.6 Enablers and Strategic Outcomes

Conversely, a number of studies highlight enablers of successful adoption. Investment in digital infrastructure, strong leadership support, and targeted training initiatives significantly increase the likelihood of effective HR analytics implementation (Shet et al., 2021). Moreover, organizations that cultivate a culture of evidence-based decision-making and transparency experience higher employee trust and smoother integration of analytics tools (Zeidan & Itani, 2020). Research also suggests that organizations that have successfully adopted HR analytics report measurable improvements in recruitment efficiency, employee engagement, and turnover prediction accuracy (Avrahami et al., 2022). Importantly, embedding analytics within strategic HRM frameworks enhances alignment with broader business goals, thereby transforming HR into a driver of organizational competitiveness (Carlucci & Schiuma, 2020).

2.7 Identified Research Gaps

Despite growing scholarship, gaps remain. First, there is limited empirical research in the Indian context, particularly in Delhi NCR where the IT/ITES sector is concentrated. Second, few studies distinguish between awareness and understanding as distinct constructs, even though this distinction is critical for effective adoption. Third, research on barriers often emphasizes technical issues but neglects cultural and ethical dimensions, which are especially relevant in emerging markets. Finally, longitudinal studies that track adoption trajectories over time are scarce, leaving questions about sustainability unanswered. This study addresses these gaps by focusing on awareness and understanding among HR professionals in Delhi NCR, analyzing both inhibitors and enablers, and providing practical recommendations.

3. RESEARCH METHODOLOGY

3.1 Research Objectives

Building on the research gaps identified in the literature, this study formulates specific objectives that guide the methodological choices outlined in this chapter. These objectives establish the scope of inquiry and inform the design, sampling strategy, instrument development, and analytical techniques adopted.

To assess the level of awareness of HR analytics tools among HR professionals.

1. To examine the extent of understanding and practical application of these tools in recruitment, performance management, and retention.
2. To identify barriers and enablers that influence the adoption of HR analytics.
3. To provide recommendations for enhancing HR analytics readiness in emerging markets.

To address these objectives, the study employed a descriptive and empirical research design, ensuring that both breadth (quantitative measures) and depth (qualitative insights) were captured. The subsequent sections detail the design, population and sampling, instrument development, and data analysis strategies adopted.

This research contributes to both theory and practice. Theoretically, it adds to the growing literature on HR analytics by distinguishing between awareness and understanding—two constructs often conflated in existing research. By situating the study in

Delhi NCR, it also offers insights into the adoption of analytics in an emerging economy context, where organizational maturity, technological infrastructure, and cultural factors differ significantly from Western economies.

3.2 Research Design

The study adopted a descriptive and empirical research design to systematically assess the awareness and understanding of HR analytics tools among HR professionals in the Delhi NCR region. A descriptive design was appropriate because the objective was not to manipulate variables but to map the current state of knowledge, practices, and barriers associated with HR analytics adoption. Empirical grounding ensured that conclusions were drawn from observed responses rather than theoretical assumptions. Such a design is consistent with previous HR analytics adoption studies in emerging markets, where mapping awareness and usage patterns provides a baseline for future interventions (Shet et al., 2021; Saxena, 2025).

Unlike exploratory case studies that rely on limited organizational examples, this design enabled data triangulation through surveys and semi-structured interviews. The combination of quantitative and qualitative elements provided both breadth (through numerical indicators) and depth (through practitioner narratives).returns if HR professionals lack the competence to interpret data and translate insights into action (Saxena, 2025).

3.3 Population and Sampling

The population of interest comprised HR professionals employed in IT, ITES, and service-oriented organizations operating in the Delhi NCR. This geographical cluster is particularly significant as it hosts a mix of multinational corporations, large domestic companies, and fast-growing start-ups. The region thus offers heterogeneity in organizational size, maturity, and HR technology adoption, making it ideal for assessing varied levels of awareness and understanding.

A purposive sampling technique was employed, targeting only those respondents actively engaged in HR roles such as recruitment, performance management, or employee engagement. This ensured that the sample consisted of practitioners directly exposed to HR analytics tools or their outcomes. A total of 50 valid responses were obtained. While modest in size, the sample provided sufficient variability across age, gender, designation, and experience, enabling subgroup analysis. Table 1 presents the demographic profile of the respondents.

Table 1: Demographic Profile of Respondents (N = 50)

Variable	Categories	Frequency	Percentage
Age Group	Below 25	19	38.00%
	25–35	13	26.00%
	35–45	16	32.00%
	45 & Above	2	4.00%
Gender	Male	28	56.00%
	Female	20	40.00%
	Other/Prefer not to say	2	4.00%
Total		50	100%

The table 1 reveals that the sample was dominated by young professionals (64% below 35 years), reflecting the demographic composition of India's HR workforce in the IT/ITES sector. Gender distribution was relatively balanced, with slightly more male respondents, aligning with industry patterns.

3.4 Instrument Development

The research instrument was a structured questionnaire designed after reviewing validated scales from previous HR analytics research (George & Kamalanabhan, 2016; Upadhyay & Khandelwal, 2018). To contextualize the items for Indian organizations, questions were refined through pilot testing and expert review.

The questionnaire had four sections:

i. **Demographic Information** – capturing age, gender, designation, HR experience, and organizational sector.
ii. **Awareness of HR Analytics (Section A)** – five Likert-scale items measured familiarity with the concept of HR analytics, knowledge of tools such as Tableau, Power BI, and SAP SuccessFactors, organizational promotion of analytics, formal training experiences, and self-learning behaviors.
iii. **Understanding and Application (Section B)** – five items measured the ability to apply analytics in recruitment, performance management, employee retention, strategic decision-making, and reported instances of actual application.
iv. **Barriers and Enablers** – additional items collected perceptions of challenges (data privacy, lack of training, resistance to change) and enabling factors (leadership support, infrastructure, organizational culture).

Responses were recorded on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), ensuring comparability across constructs.

3.5 Reliability and Validity

Instrument reliability was tested using Cronbach's alpha. Section A (Awareness) achieved an alpha of 0.886, and Section B (Understanding & Application) achieved an alpha of 0.915, both exceeding the widely accepted threshold of 0.70 (Nunnally, 1978). This indicates that the scales were highly internally consistent.

Table 2: Reliability Statistics of Constructs

Construct	Items	Cronbach's α	Interpretation
Awareness	5	0.886	High reliability
Understanding/Application	5	0.915	Excellent reliability

Validity was addressed in multiple ways. Content validity was ensured by adapting items from prior validated instruments and aligning them with the study objectives. Construct validity was established through expert review by two academics and two HR practitioners. Face validity was confirmed during pilot testing with 20 HR professionals, who affirmed that the items were relevant and comprehensible.

3.6 Data Collection Procedure

Data were collected over a two-month period using both online (Google Forms, email distribution) and offline channels through professional HR networks. A total of 65 questionnaires were distributed, and 50 complete responses were received, resulting in a response rate of 76.9%.

To complement the survey, ten semi-structured interviews were conducted with senior HR managers from large ITES organizations. These interviews provided qualitative insights into barriers such as resistance to analytics-driven decision-making and enablers such as leadership sponsorship.

Participation was voluntary, and respondents were assured of confidentiality and anonymity. No identifying information was reported, and consent was obtained at the start of each survey and interview.

3.7 Data Analysis Techniques

Quantitative data were analyzed using SPSS and MS Excel. The analysis followed a structured sequence:

i. **Descriptive statistics**: Frequencies and percentages were calculated for demographics; means and standard deviations for Likert-scale items.
ii. **Reliability analysis**: Cronbach's alpha tested the internal consistency of awareness and understanding scales.
iii. **Composite indices**: Awareness (A_mean) and Understanding (B_mean) scores were created by averaging relevant items.
iv. **Correlation analysis**: Pearson's correlation examined the relationship between awareness and understanding/application. The correlation was found to be **r = 0.798**, indicating a strong positive relationship.
v. **Group comparisons**: Independent sample t-tests compared awareness and understanding across gender. No statistically significant differences were observed ($p > 0.05$). ANOVA tested differences across experience levels, with results approaching significance ($p = 0.076$), suggesting potential trends.
vi. **Qualitative analysis**: Interview transcripts were coded thematically to identify recurring narratives around inhibitors (data quality, privacy, resistance) and enablers (training, infrastructure, leadership support).

3.8 Ethical Considerations

The research adhered to ethical standards for social science studies. Participation was voluntary, with informed consent obtained. Respondents were assured of anonymity and confidentiality, and data were stored securely. Findings are reported in aggregate to prevent identification of individuals or organizations.

The methodology was designed to balance rigor with feasibility. The use of purposive sampling ensured relevance but limited generalizability. The modest sample size reflects the difficulty of obtaining responses from busy HR professionals, yet the high reliability coefficients suggest strong instrument design. Integrating interviews with surveys enriched the findings, capturing nuances that quantitative data alone might overlook. Future research could build on this by employing longitudinal designs to track how awareness and understanding evolve as organizations mature in their analytics adoption.

4. RESULTS AND DISCUSSION

4.1 Awareness of HR Analytics

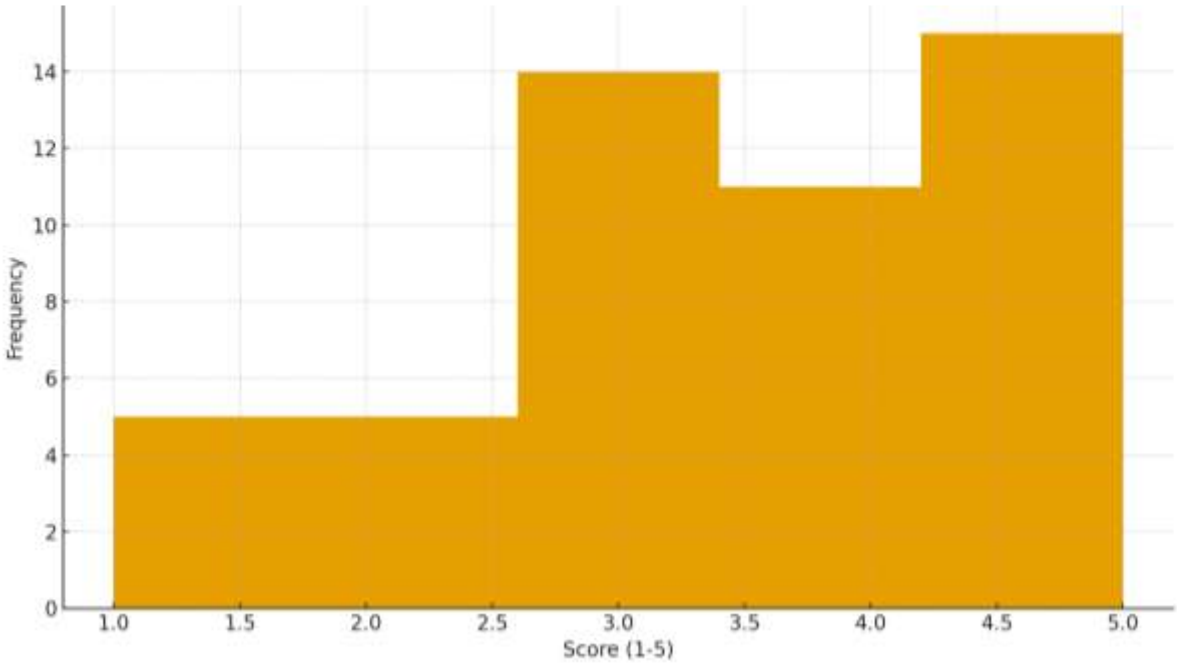
The descriptive results reveal that awareness of HR analytics is present but unevenly distributed among HR professionals in Delhi NCR. As presented in Table 3, respondents demonstrated relatively higher familiarity with the conceptual importance of HR analytics (A1: M = 3.54, SD = 1.27) than with specific tools or formal training opportunities. In practical terms, this means that while HR professionals have heard about analytics and recognize its relevance, fewer have direct exposure to tools such as Power BI, SAP SuccessFactors, Oracle HCM, or Tableau (A2: M = 3.30, SD = 1.33).

The lowest-rated awareness item concerned formal training or workshops (A4: M = 3.28, SD = 1.33). This highlights a critical capability gap: organizational training infrastructures have not kept pace with the global emphasis on data-driven HR practices (Marler & Boudreau, 2017). Interestingly, the second-highest item was self-directed learning (A5: M = 3.44, SD = 1.20), suggesting that many professionals are compensating for the absence of structured organizational training by informally educating themselves through online courses, webinars, or peer learning.

Table 3. Descriptive Statistics — Awareness (N = 50)

Code	Awareness Item	Mean	SD
A1	Familiar with HR analytics and its relevance in HR practices	3.54	1.27
A2	Awareness of analytics tools (Power BI, Tableau, SAP, Oracle)	3.3	1.33
A3	Organization promotes awareness among HR staff	3.38	1.28
A4	Formal training or workshops received	3.28	1.33
A5	Regularly update myself on trends in HR analytics	3.44	1.2
A_mean	**Composite Awareness Index**	**3.39**	**1.06**

Figure 1. Distribution of Awareness Scores (A_mean)



The histogram illustrates that most respondents fall in the neutral-to-agree zone, clustering between 3 and 4. This confirms that awareness is moderate rather than advanced. It is neither absent nor deeply embedded, indicating the first stage of HR analytics adoption maturity.

This finding resonates with studies in other emerging economies, where awareness often precedes systematic adoption (Upadhyay & Khandelwal, 2018). It also signals that organizational investment in structured training is critical, since professionals are relying heavily on informal channels to bridge gaps.

4.2 Understanding and Application

While awareness levels are moderate, application results are comparatively stronger, especially in performance management (B2: M = 3.82, SD = 1.10) and recognition of analytics' strategic role (B5: M = 3.78, SD = 1.28). These results suggest that HR professionals see analytics as more than just a dashboard exercise; they understand its potential for shaping decisions.
Recruitment analytics (B1: M = 3.46) and retention analytics (B3: M = 3.60) scored lower than performance management. This reflects practical constraints: performance management data are structured and easily accessible, while recruitment and retention involve more dynamic, contextual, and less predictable data. In practice, HR managers may find it easier to track appraisal scores or productivity metrics than to design predictive models for employee turnover.

Actual hands-on application (B4: M = 3.32) was the weakest score. This gap between "knowing" and "doing" reflects the well-documented challenge of translating awareness into routine application (Shet et al., 2021).

Table 4. Descriptive Statistics — Understanding & Application (N = 50)

Code	Understanding/Application Item	Mean	SD
B1	Application in recruitment	3.46	1.3
B2	Application in performance management	3.82	1.1
B3	Application in retention/attrition management	3.6	1.23
B4	Applied analytics in at least one HR function	3.32	1.2
B5	HR analytics critical in strategic decision-making	3.78	1.28
B_mean	**Composite Understanding/Application Index**	**3.6**	**1.06**

The relatively high scores for performance and strategy suggest that organizations recognize analytics' importance in formal systems, but actual deployment is patchy. Many organizations in India adopt a top-down "strategic narrative" around analytics without ensuring bottom-up practical implementation, creating a gap that managers must bridge.

4.3 Correlation Between Awareness and Understanding

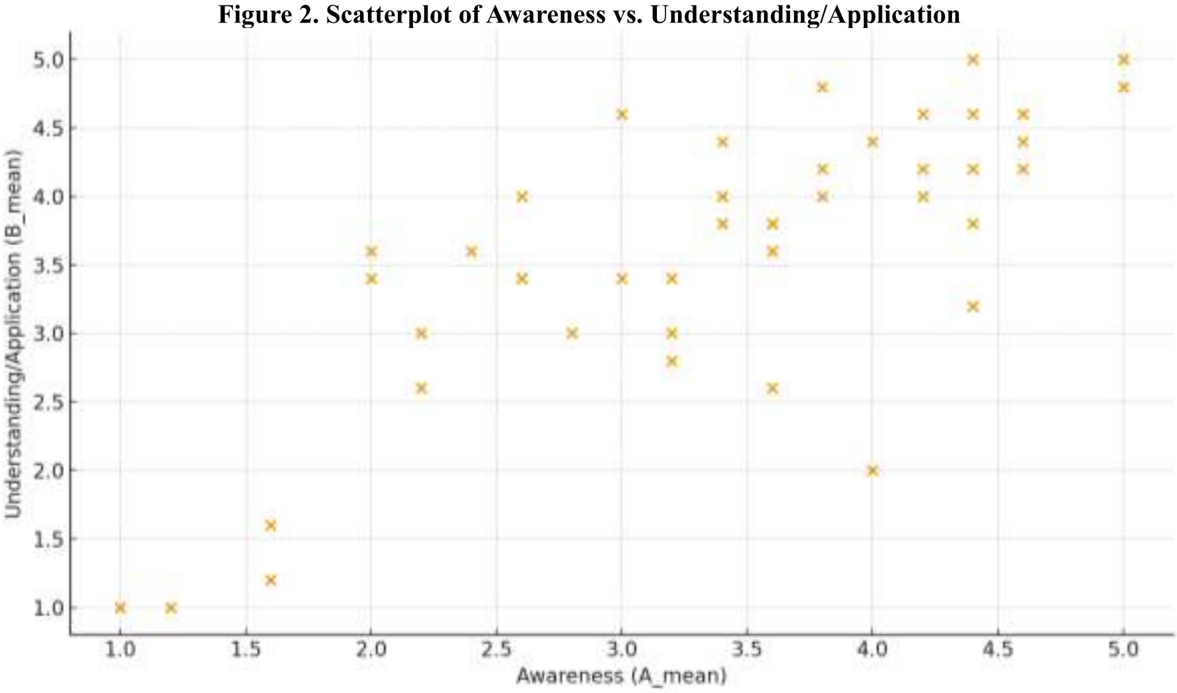
The relationship between awareness and application was tested using Pearson's correlation. The result was $r = 0.798$ ($p < 0.0001$), showing a very strong positive correlation.

Table 5. Correlation Matrix (N = 50)

Variable	A_mean	B_mean
A_mean	1	0.798**
B_mean	0.798**	1

(**p < 0.01)

Figure 2. Scatterplot of Awareness vs. Understanding/Application



This result is critical: it shows that as professionals become more aware, they are far more likely to apply analytics. Nearly two-thirds of variance in application (64%) can be explained by awareness levels. This empirically supports global research highlighting the "knowing–doing gap" in HR analytics (George & Kamalanabhan, 2016).

For HR leaders, this is not just a statistical finding—it is a call to action: building awareness through structured interventions can directly fuel adoption.

4.4 Group Differences

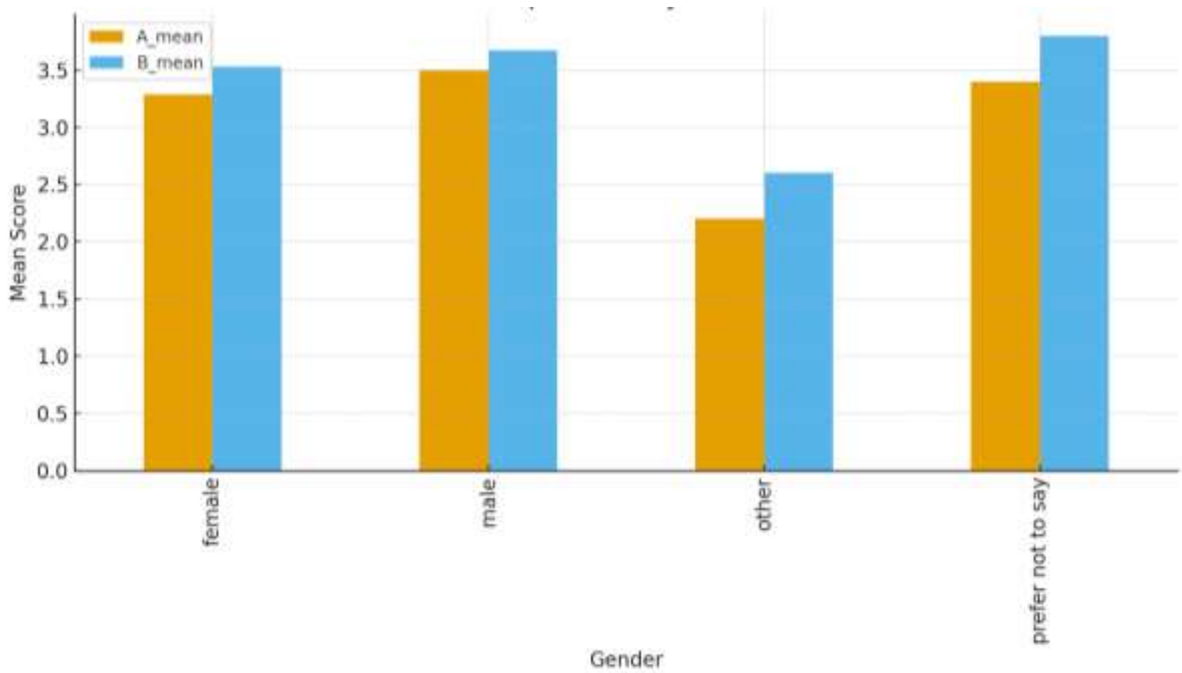
4.4.1 Gender

The gender-based t-test revealed **no significant differences** between male and female HR professionals in awareness or application ($p > 0.05$).

Table 6. Composite Means by Gender

Gender	A_mean	B_mean
Male (n=28)	3.5	3.67
Female (n=20)	3.29	3.53
Other/Prefer not to say (n=2)	2.8	3.2

Figure 3. Group Means of Awareness and Understanding by Gender



These results are encouraging. Unlike global findings where women often report lower access to technical training (Leicht-Deobald et al., 2019), this study shows gender parity in HR analytics exposure. This could reflect India's growing emphasis on equitable upskilling opportunities in HR, particularly in large IT/ITES firms.

4.4.2 HR Experience

ANOVA revealed a non-significant but suggestive trend ($F(3,46) = 2.44$, $p = 0.076$). As shown in Table 7, mean application scores rose with HR experience.

Table 7. Understanding/Application by HR Experience

HR Experience	Mean B_mean	SD	n
0–2 years	3.2	1.17	21
2–5 years	3.58	0.58	8
6–10 years	3.75	1.2	8
10+ years	4.15	0.79	13

Experienced professionals appear to deploy analytics more strategically, while junior professionals remain at an introductory stage. This reflects organizational hierarchies: senior HR staff influence policy decisions where analytics is more often invoked. These findings echo Shet et al. (2021), who noted that analytics tends to be embedded in strategic HR layers before trickling down to operational levels.

4.5 Integrated Discussion

The results collectively paint a picture of early-stage yet promising adoption of HR analytics in the Delhi NCR region. Overall, the findings highlight moderate awareness and partial application, with professionals largely understanding the importance of HR analytics but lacking structured training and consistent organizational support. While awareness of the concept and its strategic relevance is reasonably widespread, the actual translation into daily practice remains limited. A particularly noteworthy insight from the study is the strong awareness–application link: empirical evidence demonstrates that awareness forms the bedrock of application. Without adequate awareness, application tends to remain superficial, fragmented, and largely symbolic rather than transformative. Another key observation is that gender does not serve as a barrier to adoption, as men and women in the sample showed comparable levels of awareness and application. Instead, experience emerged as the differentiating factor, with senior HR professionals displaying deeper and more strategic use of analytics compared to their less-experienced peers. Furthermore, adoption appears to be performance-focused, with analytics being applied most strongly in areas where data are structured and cycles are established, such as performance management. In contrast, domains like recruitment and retention remain weaker, echoing global trends where data-rich processes tend to mature faster in analytics adoption.

The implications of these findings are significant. Organizations must move beyond slogans about "being data-driven" and instead invest in comprehensive training ecosystems that can build robust capabilities across the workforce. At the same time, HR leaders should implement tiered capability frameworks that provide introductory training for junior staff and advanced predictive modeling workshops for senior professionals. This tiered approach would ensure that analytics adoption cascades across levels rather than remaining concentrated at the top. On a broader scale, policymakers and industry bodies such as NASSCOM and SHRM India could play a vital role in supporting standardized certification programs, thereby creating a benchmark of analytics skills across organizations. Finally, firms should actively showcase success cases by embedding analytics in performance reviews, attrition prediction, and talent acquisition, as these practical demonstrations of impact can motivate wider adoption and build confidence among HR practitioners.

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