

# A PSM MODEL APPROACH TO EXAMINING THE EFFECT OF HR ANALYTICS ADOPTION ON FIRM RETURN ON INVESTMENT

**Preeti Gupta,**

Research Scholar, Glocal School Of Business & Commerce,  
Glocal University Mirzapur Pole , Saharanpur (Uttar Pradesh) India.

**Dr. Indresh Pachauri ,**

Research Supervisor, Glocal School Of Business & Commerce  
Glocal University Mirzapur Ploe, Saharanpur (Uttar Pradesh) India.

## ABSTRACT

This study examines HR adoption in Indian firms at the firm level. Propensity score matching (PSM) is used to examine data from 116 Indian BSE listed businesses for the 2020–2021 period, and linear regression analysis is then performed. Many market research agencies have predicted that the use of human resource analytics (HRA) by businesses in India and throughout the world will rise at a respectable rate. Few research, nevertheless, have clarified how disparate advantages could be caused by variations in business HR procedures. This study examines HR adoption in Indian firms at the firm level. Propensity score matching (PSM) is used to examine data from 116 Indian BSE listed businesses for the 2020–2021 period, and linear regression analysis is then performed. The outcome indicates that HR analytics

**Keywords: HR Analytics, Return of Investment (ROI), Propensity Score Matching**

## INTRODUCTION

However, the best development HR analytics approach to the integrated HR function, including recruiting, training and development, succession planning, retention, engagement, compensation, and benefits, will help to improve people-related decisions and enhance individual and organizational performance (Mishra et al., 2016). In HR analytics, empirical research is insufficient and only 16% of the organizations have reported using HR analytics. Research shows that over 60% of top management executives believe that the human resource department impacts business performance (Deloitte, 2016). Thus, the HR department can be a competitive advantage provider. The question arises how can HR provide a competitive advantage? The general psychology of any organization is that they will gain a competitive advantage by hiring the best possible talent (Nishii, 2008); however, this belief does not hold much ground considering that it's impossible to recruit such talent at a reasonable cost. However, the best development HR analytics approach to the integrated HR function, including recruiting, training and development, succession planning, retention, engagement, compensation, and benefits, will help to improve people-related decisions and enhance individual and organizational performance (Mishra et

al., 2016). In HR analytics, empirical research is insufficient, and only 16% of the organisations have reported using HR analytics. There is limited scientific evidence to favor the adoption of HR analytics (Marler & Boudreau, 2017; Ban-Gal, 2019).

HR analytics is a strategic investment decision taken by an organisation to empower HR professionals and unlock valuable insights to drive intelligent business decisions. Therefore, it is critical to succeed in the dynamic business environment, shape business outcomes, and achieve goals (Ahmad, 2020). It is observed that while more and more organisations are showing interest in HR analytics, they have little research support to guide the adoption and unlock value. Most of the studies are based on a single organisation or are case-specific, thereby limiting the generalization of results. Despite the acceptance of HR analytics, scientific studies on the subject are limited (Ban- Gal, 2019; Kremer, 2018; Van Heuvel & Bondarouk, 2016). Extant research tests an association between HR analytics and business outcomes (Marler and Boudreau, 2017). However, it is still complicated for organizations to decide whether HR analytics adoption will give a higher return on investment or directly impact the business outcome.

Quantitative and qualitative measurement of HR analytics adoption outcomes can assist organizations in meeting their business goals (Fitz-Enz & John Mattox, 2014). HR analytics adoption in organisations is the decision to invest in information technology (IT) and human capital (Aral et al., 2012). Dewan & Kraemer (2000) and Pohjola (2001) suggest that IT investments in developing countries have an insignificant impact on productivity benefits. However, these investments have increased considerably in developing countries such as India. Drábek et al. (2017) suggest that investment in HR capital is a crucial factor for the development of an organisation. Brynjolfsson et al. (2002) indicate that investment of one rupee in IT is associated with ten rupees of market value, whereas the rest is attributed to complementary business investment. Marler and Boudreau (2017) analyse 14 existing studies and find only one study provided empirical evidence linking HR analytics and company performance. This empirical result indicates that a business has to spend money on human capital development and IT to maximize the return on investment. Benefits of investing in human capital development include increased employee satisfaction, retention ratio, employee engagement, client engagement, organisational communication, and a more credible company culture (Jeanetta, 2019). In recent times, HR analytics has gained significant attention from scholars and researchers to capture the factors that determine the organizational level of HR analytics adoption. This paper studies the determinants of HR analytics adoption scientifically at the organisation level using propensity score matching, followed by ordinary least square (OLS) regression. This scientific study will help organisations in strategic decision-making for investment in adopting HR analytics.

## **LITERATURE REVIEW**

### **HR Analytics and Return on Investment**

The integration of information technology using data in the area of HR is referred to as HR analytics, people

analytics, and workforce analytics. These terms are interchangeably used for HR analytics (Van Heuvel & Bondarouk, 2017). HR analytics has become a popular instrument for successfully using data in the HR department to predict investment return and gain a comparative advantage (Boudreau & Ramstad, 2005). Even HR professionals perceive HR analytics as a tool that enables data-driven decision-making to achieve successful business outcomes (Jones, 2014). Marler and Boudreau (2017) define HR analytics as "an HR practice enabled by information technology (IT) that uses descriptive, visual, and statistical analyses of data related to HR processes, human capital, organizational performance, and external economic benchmarks to establish business impact and enable data-driven decision-making." This implies that HR analytics plays a crucial role in enabling an organisation to maintain a competitive advantage. Even the rising interest in HR analytics shows limited scientific evidence to favour its adoption (Rasmussen & Ulrich, 2015; Nair, 2018). HR analytics adoption for an organisation is a strategic IT investment decision. Ravichandran et al. (2009) suggest that while deciding on IT investment, the decision-makers must analyse factors like the company's financial condition, IT spending of competitors, and firm image, apart from the economic benefits. Thus, we hypothesize that adopting HR analytics would have a higher return on investment.

Hypothesis: HR analytics adoption in organisations is associated with a higher return on investment.

#### Research Objective

The goal of the current study is to give an organization scientific proof so that it can decide if implementing HR analytics would give them the required competitive edge. Secondly, it contrasts any real variations in ROI (return on investment) between companies using HR analytics and those who haven't.

#### Data and Research Design

This research paper examines the hypothesized relationship using the Indian firms listed in the BSE over the period of 2020 to 2021. Because in the past five years, a nearly 80% rise in HR analytics professionals in India was the highest growth in the Asia-Pacific region (Linkedin, 2018) & (Ians, 2018). However, the statistical data shows that only about 2% of public listed companies have opted for HR analytics practices. The reason to select the financial year 2020-21 is to capture the adequate treatment difference in economic outcomes on organisations. The difference will help the new organisations make strategic decisions on HR analytics adoption and how it affects organisational performance.

The data is obtained from the Centre for Monitoring Indian Economy Pvt. Ltd (CMIE) Prowess database has 4754 listed firms in the BSE for the financial year 2020-2021, 2754 of which have complete data for all the required variables used in this study. The data is then analysed using Propensity score matching to test for evidence on the causal relationship between HR analytics adoption and return on investment.

Propensity score matching (PSM) allows matching firms that have adopted HR analytics to those that have not done so. The matching is done to observe the company characterises balance between these two groups. The

difference in return on investment between firms with HR analytics and the match comparison group is the impact of HR analytics adoption.

#### Modeling: PSM

Ravichandran et al. (2009) suggested that adopting HR analytics is a strategic decision in HR capital and IT investment because decision-makers analyse and discuss the organisational financial conditions apart from the economic benefits. Therefore, financial considerations are important when deciding on HR analytics adoption. This study uses the propensity score matching method (Heckman & Robb, 1986; Heckman, Ichimura, & Todd, 1998) to determine the causal relationship between HR analytics adoption and return on investment. This is because an organisation's HR analytics adoption is endogenous, and its financial condition can influence both HR analytics adoption and return on investment.

We estimate the firm's propensity to adopt HR analytics on listed BSE firms by estimating the average effect of treatment using three steps. Firstly, the probability of HR analytics adoption is calculated, giving each firm a balancing score. Secondly, produced balance scores are used to find a perfect comparison group from 2696 firms that did not adopt HR analytics. The mean difference in return on investment between HR analytics adopted firm and comparison group. Lastly, the regression of the return on investment on covariates is done to find a matched sample's treatment effect.

Balance scores are calculated using the logistic regression model of probability of HR analytics adoption  $P(A)$  as a function of the control variable ( $X_i$ ) that consists of the investment criteria (Payout ratio), firm size (log of employee number), employee productivity (employee utilisation rate) and industry (dummy variable for each industry classified based on National Industrial Classification).

$$P(A = 1|X_i) = 1/(1 + e^{-(\beta_0 + \beta_i X_i)}).$$

Based on past studies, covariates included in the balance score model are selected. It is found that HR analytics adoption and investment decisions are significantly associated with payout ratio, firm size, employee utilization rate, and industry (Husna & Satria, 2019; Slim, 2019; Madhavi & Siva, 2016; Raffiee & Byun, 2020; Witte, 2016).

The payout ratio, in particular, is found to be an important factor in the investment decision. Husna & Satria (2019) suggest that the payout ratio is negatively correlated with investment, implying that the higher the payout ratio, the lower the investment, and the lower the payout ratio, the higher the investment. As HR analytics adoption is a strategic investment decision, companies with a lower payout ratio are likely to invest more.

Firm size is another factor highly associated with HR analytics adoption; Sierra-Cedar (2016) finds that large and mid-sized firms are more likely to invest in HR analytics adoption. Slim (2019) finds that HR analytics adoption is associated with firm size. The larger the firm, the more likely it to adopt HR analytics.

Regarding human resource management, employee utilisation rate helps in forecasting, resource optimization,

and other HR functions. Madhavi & Shiva (2016) state that measurement of HR analytics improves employee utilisation, which is related to human resources complementarity (Raffiee & Byun, 2020). Firms adopting HR analytics are more likely to have complementarity.

Markets research reports by Sierra-Cedar and Deloitte have found that the adoption of HR analytics greatly influences the industry. Financial services, high-tech and retails, and wholesale businesses show the highest adoption rate; the lowest is in the case of agriculture, mining, and construction. Witte (2016) also finds that HR analytics adoption is associated with the type of industry.

We use the nearest neighbourhood matching method to identify the organisations showing an equal propensity to adopt HR analytics. Using the nearest neighbouring method of Propensity score matching showed 58 matches (control-treated), that is, 58 firms that have not adopted HR analytics, and 58 firms (treated firm) that have adopted them. So, we had a total of 116 matched firms from the total of 2754 firms considered for the study. The sample is not affected by selection bias to analyse the relationship between return on investment and HR analytics propensity adoption.

After arriving at the 116 matched firm number, we use the following empirical specification to estimate the average treatment effect on treated (ATT):

$$R_i = \alpha + \beta A_i + \gamma X_i + \varepsilon_i,$$

where  $R_i$  is the dependent variable which refers to the firm's return on investment using two indicators, that is, return on capital employed (ROCE) and return on asset (ROA). The variable  $A_i$  is the treatment variable of HR analytics adoption, while  $X_i$  is a vector of firm-level control variables, such as the number of employees (EMP), debt-equity ratio (DER), firm age (AGE), square of firm age (AGES), payout ratio (PR), and employee utilization rate (EUR).  $\varepsilon_i$  is a normally distributed mean-zero error term.

## RESULTS

### Statistical Summary

Summary statistics indicate that HR analytics firms (N=58) and all the potential comparison firms (N=2696) are unbalanced in every covariate used in the logistic regression to estimate the balance score (Table 1). The organisation with HR analytics tends to have a greater payout ratio, the number of employees, firm age, and less employee utilisation rate than the organisation that has not adopted HR analytics. The differences are significant at the level of 5%. HR analytics-adopted firms have higher returns on investment than firms not opted for HR analytics in the full sample, mainly attributable to greater gross profit and less debt-equity ratio.

Table 1. Descriptive Statistics for Propensity Score Matching, Full Sample Before Matching

Full Sample (N=2754)	Firms with HR Analytics (N=58)	Firms Without HR Analytics (N=2696)
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Variable	Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max	Mean Difference
<b>Outcomes Variable</b>													
ROCE	0.04	0.135	-1.696	0.94	0.129	0.165	0.202	0.834	0.038	0.133	-1.696	0.94	0.091 ***
ROA	0.029	0.094	-1.189	0.79	0.083	0.097	0.146	0.342	0.028	0.093	-1.189	0.79	0.055 ***
<b>Control Variable</b>													
PR	0.084	0.499	-7.609	15.385	0.279	1.133	0.842	8.527	0.08	0.476	-7.609	15.385	0.199 *
DER	1.256	7.451	0	286.56	0.965	2.396	0	14.47	1.262	7.523	0	286.56	0.297 ***
GP	0.313	0.824	30.45	3.582	0.539	0.247	0.081	0.993	0.308	0.831	30.45	3.582	0.231 ***
AGE	35.37	19.666	2	156	42.53	28.527	7	117	35.21	19.409	2	156	7.32 **
AGES	1637.3	2186.84	4	24336	2608.91	3370.23	49	13689	1616.4	2150.39	4	24336	992.516 **
EMP	2.252	1.103	0.301	5.652	3.867	0.947	1.079	5.652	2.218	1.08	0.301	5.412	1.649 ***
EUR	32.279	170.348	-4.74	6218.69	12.947	13.919	1.61	70.35	32.695	172.136	-4.74	6218.69	19.748 ***
EURS	30049.93	787633.03	0	38672105.32	358	854.19	2.59	4949.12	30688.7	796051.18	0	38672105.32	30330.7 **

\*Statistically significant difference \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 (Firm with and without Hr analytics before Propensity Score Match)

After matching, we balance all covariates between the treatment group using the nearest neighbour matching . Firms in the matched sample have significantly higher returns on investment, gross profit, number of employees, firm age, and lesser debt-equity ratio than the entire sample. This is expected since firms adopt HR analytics with higher wealth and less debt than the whole sample. Thus, to match HR analytics firms with comparable control firms, the match samples must be the same as those of HR analytics firms. The result in Table 2 shows an insignificant difference between the control variable and the balanced mean.

Balancing test score indicates that the matched sample is similar between HR analytics firms and the control group (Without HR analytics) firms. The balancing test includes all variables used to estimate the propensity score (Payout ratio, number of employees, employee utilisation rate, and industry as a dummy) and some additional variables (Debt equity ratio, Gross profit Ratio, and Firmage). Return on investment indicators differ significantly between HR analytics firms and the control group firms, and all control variables achieve balance with an insignificant difference. Therefore, the selected control group seems to be suitable. This result shows that the average treatment effect on treated (ATT) estimates provides a credible measure of the causal effect that HR analytics adoption has on investment return.

### Causal Relationship Evidence

The average treatment effect (ATT) is estimated using regression analytics on the matched sample. The result suggests a causal relationship between HR analytics adoption and returns on investment. HR analytics adoption enables a firm to increase return on investment by an average of 6.2% return on capital employed and 3.2 % return on the assets, as reported in Table 2. It should be noted that these increments are in relation to HR analytics firms rather than without HR analytics firms.

Table 2. Estimation of Average Treatment Effect on Treated (ATT)

	ROA	ROCE
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	Coefficient	Std. Error	Coefficient	Std. Error
HR Analytics Adoption (Dummy)	0.033**	-0.014	0.062**	-0.024
Number of Employee	0.022***	-0.008	0.027**	-0.014
Debt Equity Ratio	-0.014***	-0.004	-0.022***	-0.007
Firm Age	0.000	-0.001	0.002	-0.002
Firm Age Square	0.000	0.000	0.000	0.000
Gross Profit Ratio	-0.042	-0.027	-0.082*	-0.048
Payout Ratio	-0.001	0.004	-0.002	0.007
Employee utilisation rate	0.001**	0.001	0.001	0.001
Constant	0.014	-0.041	0.021	-0.072
Observations	116		116	
R-squared	0.276		0.238	

\*Statistically significant \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

## CONCLUSION

A corporate organization is increasingly focused on maximizing resource utilization to obtain a competitive advantage in the fast-paced commercial world of today. Each organization gains vital value from its human resources. Thus, it is imperative to guarantee the best possible use of human resources. In order to promote the finest HR decision-making, support organizational growth, and provide the much-needed return on investment for its HR technology, a number of businesses have adopted the latest HR analytics method, which is an evidence-based strategy. The adoption of HR analytics and return on investment in Indian-listed companies are the subjects of this study's scientific investigation. According to our findings, implementing HR analytics increases return on investment. This result is consistent with previous research that links the use of HR analytics to business performance (Ben-Gal, 2020; Marler & Boudreau, Overall, our results present some implications for HR investment decisions. Statistical data shows that only about 2% of public listed companies have opted for HR analytics practices. Our findings suggest that HR analytics adoption is a viable approach to achieving competitive advantage through investment return. The push toward HR analytics adoption in India is thus, a step in right direction.

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