Project Dissertation Report on

HR Analytics in a Corporate ecosystem

Submitted by

Rajat Prasad Diwakar
Roll No: 2K19/MBA/073

Under the Guidance of

Dr. Sonal Thukral
Delhi School of Management

DELHI SCHOOL OF MANAGEMENT
Delhi Technological University
Bawana Road, Delhi – 110042

CERTIFICATE

This is to certify that the work titled **'HR Analytics in the Corporate Ecosystem'** as part of the final year Major Research Project submitted by Rajat Prasad Diwakar in the 4th Semester of MBA, Delhi School of Management, Delhi Technological University during January-May 2021 is his original work and has not been submitted anywhere else for the award of any credits/ degree whatsoever.

The project is submitted to Delhi School of Management, Delhi Technological University in partial fulfillment of the requirement for the award of the degree ofMaster of Business Administration.

Dr. Sonal Thukral
Faculty Advisor

Dr. Archana Singh
Head of Department (DSM, DTU)

DECLARATION

I hereby declare that the work titled **'HR Analytics in the Corporate Ecosystem'** as part of the final year Major Research Project submitted by me in the 4th Semester of MBA, Delhi School of Management, Delhi Technological University, during January-May 2021 under the guidance of Prof. Sonal Thukral is my original work and has not been submitted anywhere else.

The report has been written by me in my own words and not copied from elsewhere. Anything that appears in this report which is not my original work has been duly and appropriately referred/ cited/ acknowledged.

Rajat Prasad Diwakar
(Roll No 2K19/MBA/073)

ACKNOWLEDGMENT

It is a great pleasure for me to acknowledge the kind of help and guidance received during the research work. I would like to thank my faculty advisor Prof. Sonal Thukral, who helped me to take up the topic **'HR Analytics in the Corporate Ecosystem'** and guided me to complete this project properly. The project provided me with an excellent opportunity to explore the areas of Economics and Analytics.

I am highly indebted to Delhi School of Management, Delhi Technological University for giving me an opportunity to work on this project. Lastly, I would like to express my gratitude to all the honorable faculty members for sharing their experience and expertise on this project.

I have put all my efforts to ensure that the project is completed in the best possible manner and also ensured that the project is error-free.

Rajat Prasad Diwakar

(Roll No.: 2K19/MBA/073)

ABSTRACT

There is a great scope for management of the human resources present within the ecosystem of an organisation through the use of analytics. Functions in a corporate environment relies on quantitative measurements defined by the pre-requisite techniques identified by the industry, which allows them to identify, measure, analyse, & take corrective measures to increase their efficiency or productivity. As Human resource management has evolved into the spine of an organisation, as it is the only field of study that bridges the gap between the performance of their employees and the strategic objectives (Consolidation of Mission, Vision, & Objectives) of the organisation. Thus, Human Resource Analytics can provide a surgical insight over the general and complex functions of the Human resource managers, allowing them to effectively initiate a micro and macro strategy, and quantitatively measure the hypothesis, eliminating the possibilities of elements of the personal bias defined by an Individual. This paper tries to understand the methodologies and strategies that can be used by Human Resource Analysts to use Statistical methodologies and HR Metrics to identify, analyse, & effectively improve the functions of Human Resource Management through *Data Integration, Workforce Analysis & Insight Generation*.

TABLE OF CONTENTS

Chapter 1

1. Introduction

Use of Human Resource analytics is evolving the structure of operations of a corporate ecosystem which conversely affects the resource strategies. A 2015 Economist Intelligence Unit Survey identified that the 82% of the corporations will adapt Data Science, Statistical Science & Big Data within cockles of Human Resource departments in the upcoming 5-6 years. CEO's & Managers are recognising the importance of talent-related data which provides inference for the management of talent acquisition and recruitment, retention, & resource management. Human resource analytics in tandem with people analytics & workforce analytics is used as a cast to structure the Organisation's Strategy.

1.1. Background

Research and supporting evidence defined in the research conducted by IBM Workforce Analytics& Economic Intelligence Unit (2014) provides a surgical insight over the overwhelming increase of the use of 'Big Data' in the Human Resource domain. The Corporations are transitioning from an intuition-based decision maker to data-driven decision maker, as the use of data has become more evident within all of the generic & resourceful functions of an organisation, and the use of human resource analytics is an obvious reflection of the overall trend. Acknowledging the entrepreneurial trend within the cumulative industry for data analytics & that it leads to a competitive advantage within the knowledge economy, thus, data defined & derived decisions provide an asset to the organisation to improve their productivity, efficiency, rate of error, & effective business outcomes.

Human resource Department, Data dashboards are used to identify, analyse, & act through the means of evaluation of HR Metrics defined with respect to the culture, mission-vision, & objectives of the organisation, which essentially allows them to improve the strategies identified by senior executives. It allows the organisation's executives to identify, quantify & classify the productivity of its workers/employees, trough which they can derive multiple inferences such as, Return-On-Investment of its Workforce, Retention rate, Attrition rates, Requirements & Needs of the respective department, etc.

Predictive Analytics uses data derived through historical information to identify and analyse trends and derive likelihoods of the future outcomes. Through the means of predictive modelling, it will allow the organisation to identify the employees who are most likely to resign in the short term, & hinder the turnover rate through preventive measures by the HR Executives. Furthermore, it also allows the organisation to upgrade their talent acquisition strategies through monitoring HR Metrics of potential employees by identifying their suitability and computing their loyalty.

Forecasting Models, analysis of predefined structures of decisions within the respective domain that leads to a consecutive outcome, thus identifying a trend defined through the nodes of decision of making process to predict/forecast a possible outcome by calculating measurable inputs. It allows the HR Executives or Analysts to forecast employee demand & factors of retention & recruitment.

Human Resource analytics can be consolidated into few steps:

a. Data Integration & Identification
b. Workforce/Organisational Analysis
c. Strategic Insights

Human Resource Analytics includes generic levels of their analytical maturity which are defined as follows:

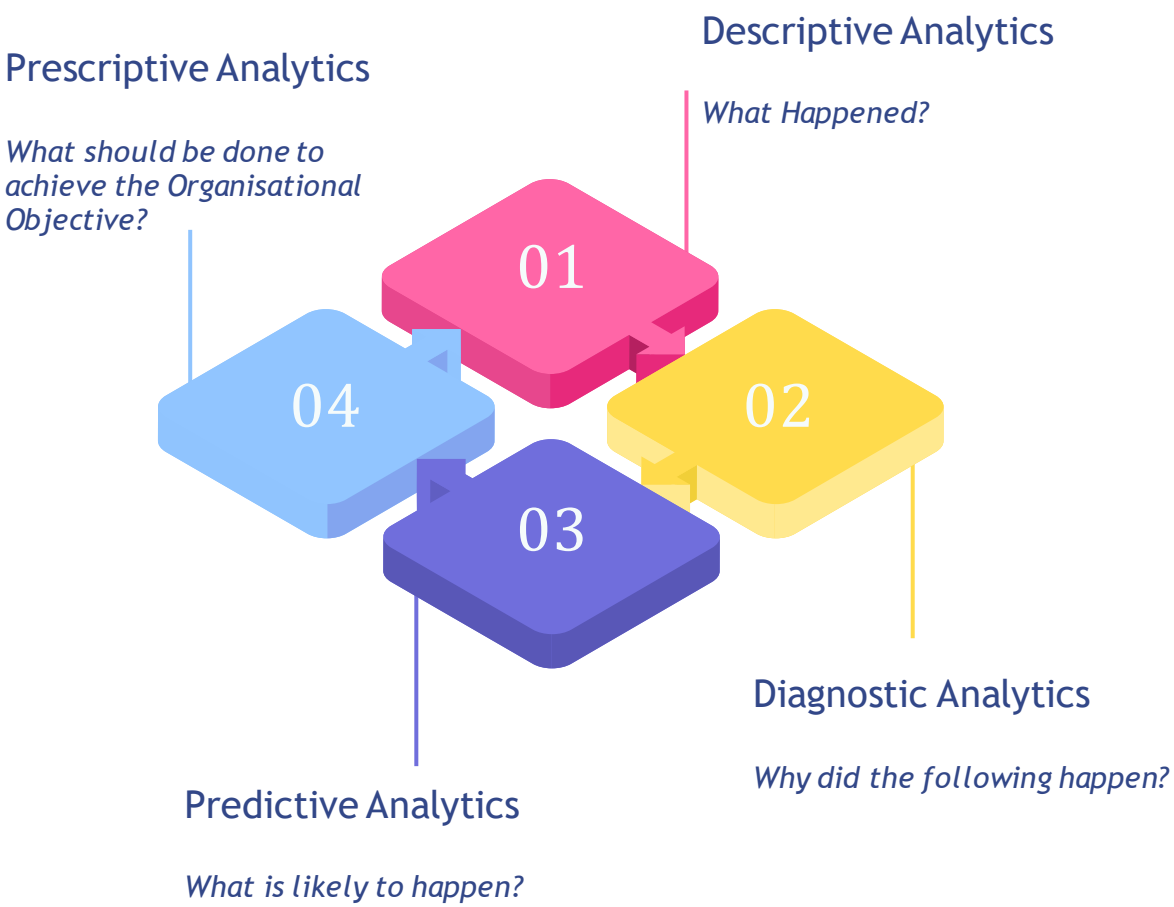


Figure 1. Process of Decision Analytics

I. Descriptive Analytics: The process has Marginal business benefits, & it is used to process gap identification within the corporate structure. Using organisation's data to create & identify key metrics.

II. Diagnostic Analytics: Focus is to understand *Why Something Happened?* It is a process of proactive consumption. Aim is to identify the reasons & facts which resulted in a respective outcome. It provides significant improvement from status quo & data backed management.

III. Predictive Analytics: *What will Happen?* It identifies the future outcomes through mathematical models such as linear regression, multi linear regression, Neural Networks to evaluate the impact of variables that affect the objectives of the given organisation. It is the process of proactive decisions.

IV. Prescriptive Analytics: Derive strategic information derived through predictive analytics is used to define strategies and objectives in an organisation. It aims at *What should I do to achieve organisational goal?* It analysis the information derived through mathematical models & identifies the best possible course of action for achieving organisational objectives. It is a spontaneous process of proactive action.

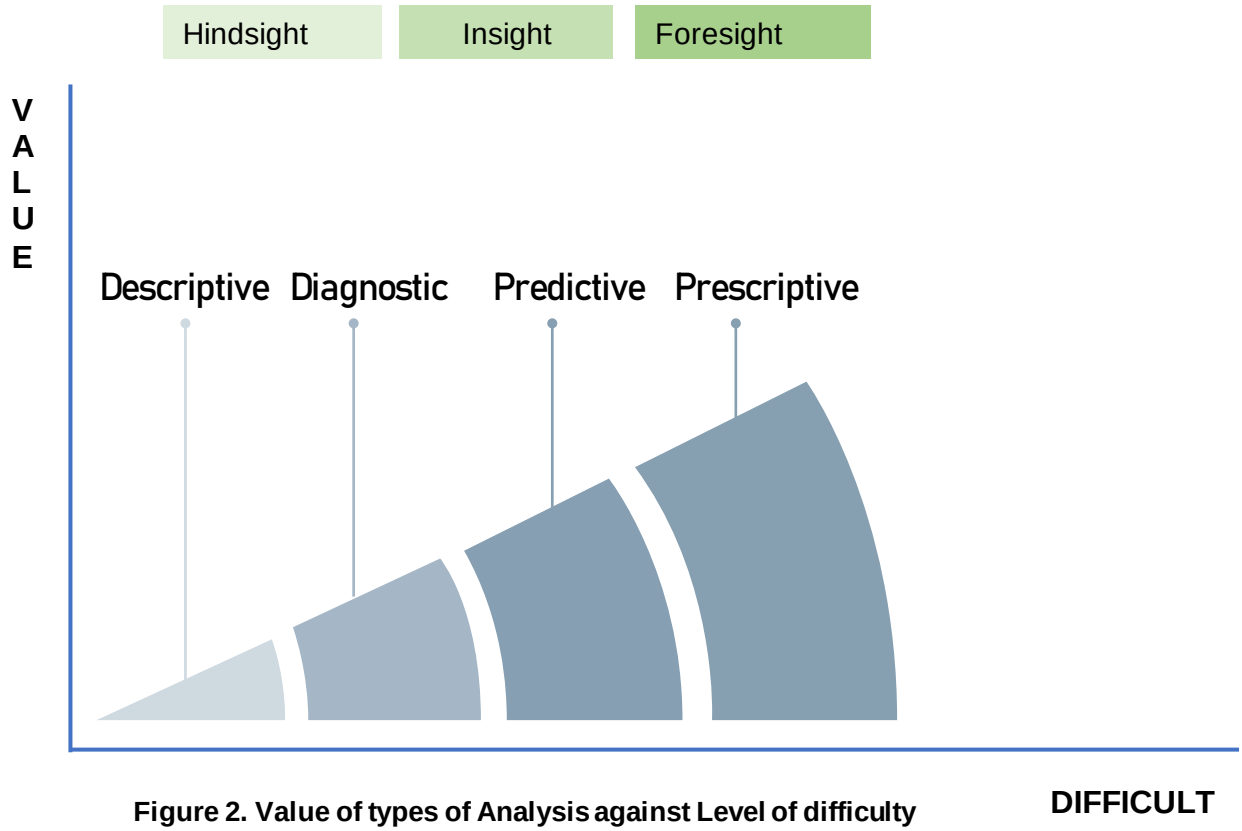


Figure 2. Value of types of Analysis against Level of difficulty

HR Metrics:

HR Metrics refers to the system of data that is used to measure the affect over an organisation through different variables identified & quantified across sectors & industries which are used to track their human capital & resource strategies.

There are multiple HR Metrics & most of them are in the form of ratios & they differ across industries. The ratios such as cost per hire, cost per external hire, attrition rate, offer acceptance rate etc are few types of HR metrics. These metrics are used to evaluate performance of an employee across different departments and highlights the effectiveness of an individual, thus, the following is defined through dashboards & organisational summary reports.

1.2. Objectives of the Research

The major objectives to carry out the respective research are:

- To understand the use of HR Analytics.
- To understand the evaluation techniques for HR Metrics.
- To find how HR Analytics affects the organisational objectives & strategies.

1.3. Scope of the Research

Overview of developments & research identified in the respective research, examines the theoretical underpinnings of Human Resource Analytics. As the corporate ecosystem is evolving with the changes caused in the 21st century through the catalyst of Big Data and data analytics, which resulted in the Intuitive based system to dissolve within the data driven revolution.

1.4. Structure of the Research

Chapter 1 discusses the introduction, followed by chapter 2 that brings out a review of the existing literature about the HR Analytics & marketing trends and observation regarding the workforce analytics. Chapter 3 presents the research methodology discussing the tool and techniques used. Chapter 4 brings out the analysis followed by chapter 5 recommendations and conclusion. Finally, chapter 6 presents the limitations and scope of future research. Chapter 7 presents an executive summary of the research paper.

Chapter 2

2. Literature Review

"Use of Workforce Analytics for a competitive advantage"
-by Economist Intelligence Unit report (2014), Gut & Gigabyte

According to the report defined by IBM Kenexa & Economist Intelligence Unit, In 2014, the number of intuition and experience-based decisions were twice in magnitude with respect to the number of strategies identified through data-driven analysis. Thus, the respective highlights that the multitudes of functions (either arbitrary or eventual) in relation with different domains of the corporation (finance, marketing, human resource, operations etc.), still relies over the traditional methodology of decision making. CEO's & Executives are trying the absorb & understand the potential of Big Data & the effectiveness of the Analytical Revolution with its foundation incorporated into Big Data. The Overview of development in the field of technological interface within the corporate suggests that the quantification, identification & analysis of data generates positive implications for the organisation.

"At the beginning of the decade, human resource analytics was not part of the language of the business. Today at the end of the decade, a google search will produce 1.5 million results"- Alec Levenson, University of Southern California.

Workforce Analytics: The respective term can be defined as the use of mathematical-statistical models like KNN, Neural Networks, Regression etc., in order to evaluate the worker/employee's effectiveness present within the corporation, thus allowing the hierarchical executives to improve organisational strategies to allocate human resource capital within the generic domains of the firm in order to increase the gross effectiveness & efficiency.

More than 3/4th of the total organisations in the world are using analytical designs structured through big data in current corporate atmosphere. Furthermore, the pandemic has shifted the gears towards the acceleration of use of data analytics within the domains of their respective industry & sector.

The financial crisis of 2008 & 2009 forced the organisation to invest in the definitive analytical units & the importance of big data. It compelled organisation to internally improve the efficacy of organisation rather than being dependent over the external economic environment, through internal activities & fundamental changes within the cockles of their business architecture. Thus, Human resource Analytics evolved into a logical component which was directly proportional to the efficiency & productivity of the cumulative system, irrespective of the market turmoil accompanied by the outlandish economic state. However, according to the research published by Tata Consultancy Services (Indian IT Advisory & Consultation firm) highlights

the use of Big data & Analytics is comparatively low in Human Resource analytics as opposed to other functions of organisations- Marketing, finance, operations, sales, customer services, legal administration, distribution & logistics, manufacturing & production, and Research and development.

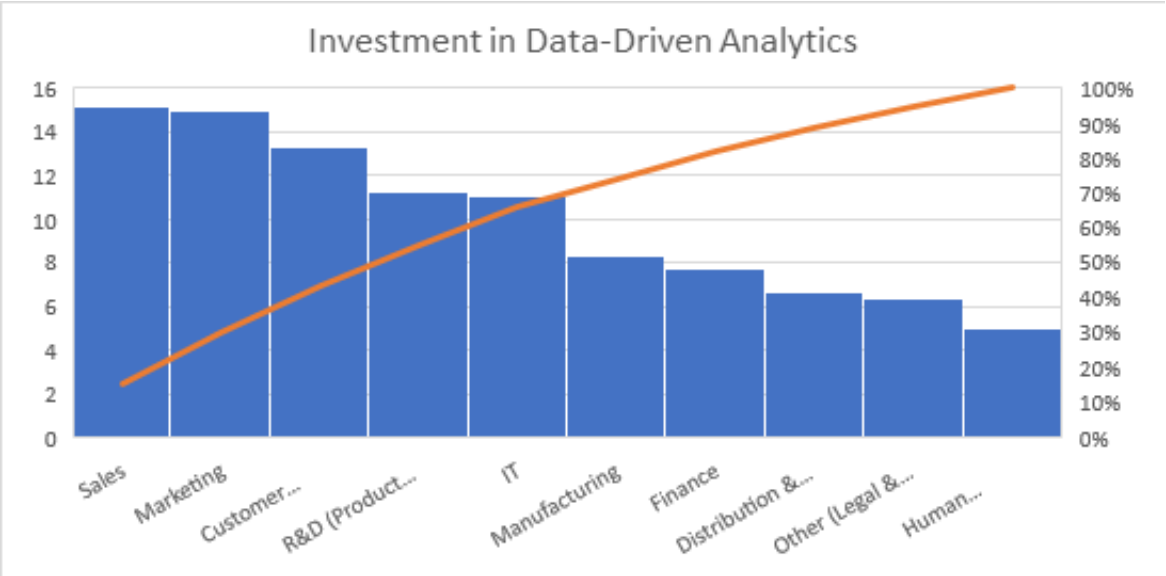


Figure 3. Investment in data driven analytics

Functions	Human Resource	Other (Legal & procurement)	Distribution & Logistics	Finance	Manufacturing	R&D (Product Development, Engineeri	IT	Customer Service	Marketing	Sales
Percentage of Total investment in Big data analytics	5	6.4	6.7	7.7	8.3	11.3	11.1	13.3	15	15.2

Table 1. Percentage of Investment in different functions of organisation

Deficiency in Information recognised by the CEO's & Executives of the current industries across the variety of sectors for workforce analytics has been highlighted in the graph defined below based upon the research conducted by the PwC Annual Global CEO Survey 2014. The following research identified that the data driven architecture used for HR Metrics is a fairly new concept, & furthermore requires more development before it can be adopted by the top tier/fortune 500 organisation, as the respective instils changes within the culture of the organisation & the internal anatomy of organisational strategies.

Dexterous Data:

For an organisation to adopt data analytics into the domains of Human Resource Management, the data has to be well-structured & well-defined, which can allow executives to create a meaningful conclusion & thereby, yield an efficient productive impact. The Corporate industries that understand the value of the need for Human Resource Analytics and big data are currently working on cloud platforms & database management systems in order to provide the intelligible data in a palatable format for the respective domains of organisation, followed by extreme scrutiny. Collection of information is one of

the most challenging tasks for the data driven revolution, as it is affected by a multitude of factors, thus creating a severe imbalance in its fault tolerance. However, Executives should realise that the quality of data & it's derived inference is as good as its analyst, thus, it should only be treated as a tool rather than a functional engine for the organisation.

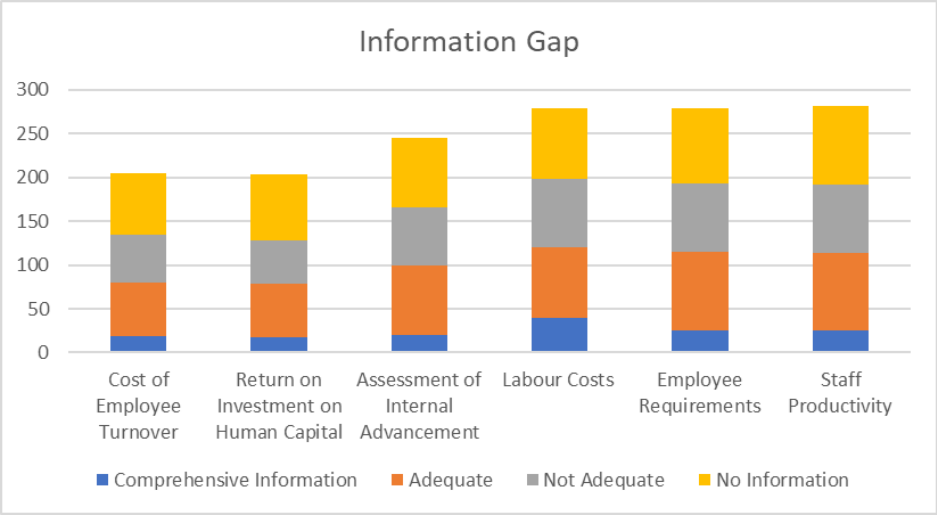


Figure 4. Information Gap

Executives of an organisation use data to classify & analyse the current status of their firm but they also require to understand the future output of their organisation, based upon the historical data available, i.e., Prescriptive Analytics. Prescriptive analytics & forecasting models can help identify appropriate conclusions with the efficient use of human resource capital that can help solve generic Human resource challenges, along with Organisational Strategies, & development of competitive edge at the same time.

The potential for relative benefits and advantages that can be yielded through big data and data driven analytics to understand & manage its human capital & human resources are defined as follows:

Figure 5. Benefits of Big Data

Factors that the executives believe that effects the efficiency & productivity of the organisation directly according to the Deloitte Survey-High Impact Talent Analytics:

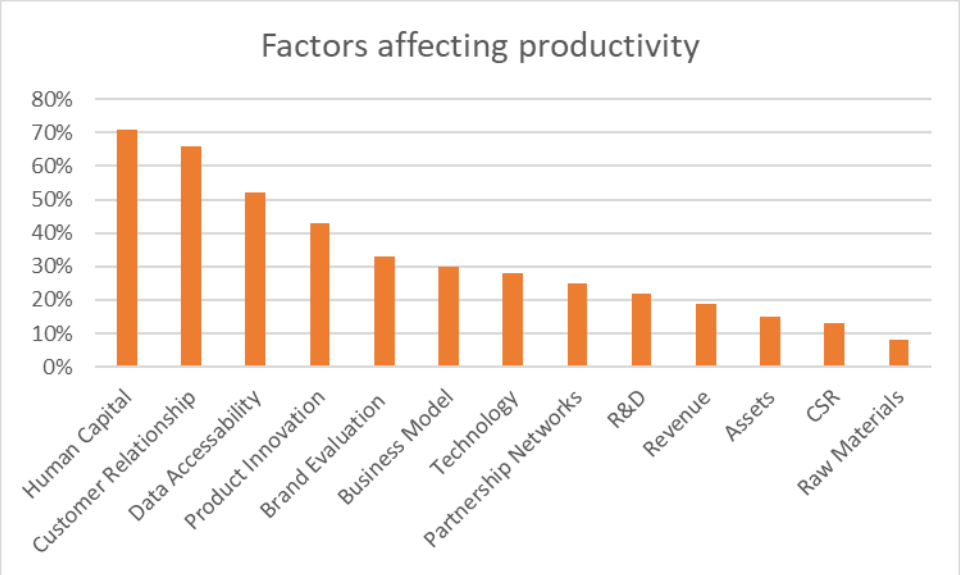


Figure 6. Factors that executives believe that affect productivity

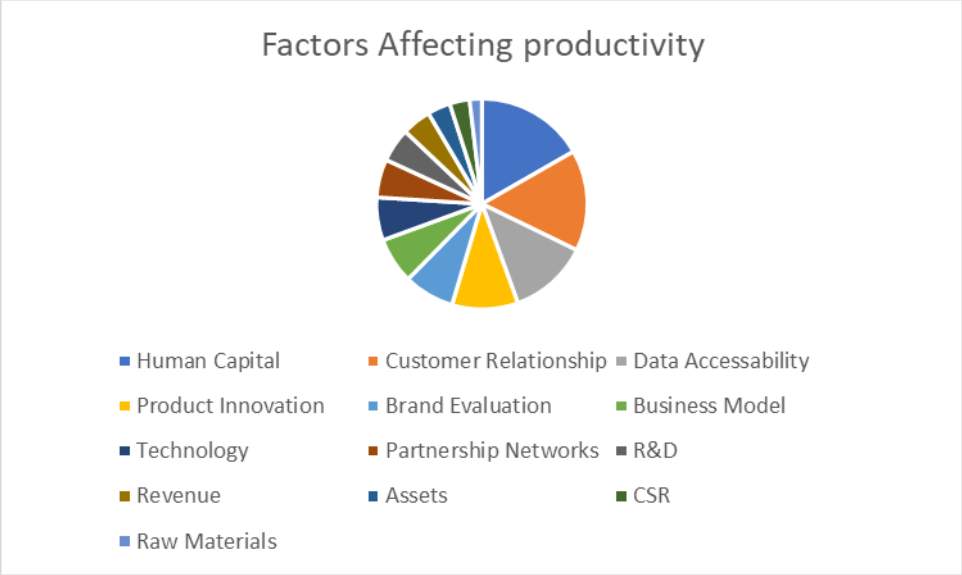


Figure 7. Pie Chart of the factors that affect productivity

As per the research- Datafication of HR, by Deloitte University Press: the results identified in the study highlights the effectiveness of data developed organisation which were classified into 4 different categories of Level 1, Level 2, Level 3, & Level 4 based upon the magnitude of big data used within the corporate strategies.

Thus, Classification of Organisation was based on the nature & level of analytics used within the domains of their respective system (Including Marketing, Finance, HR, Sales, Operations, IT, Technology, etc.):

- Level 1: Reactive-Operational Documentation
- Level 2: Proactive Advanced Reporting
- Level 3: Strategic Analytical Decisions
- Level 4: Predictive Analytics & Forecasting Models

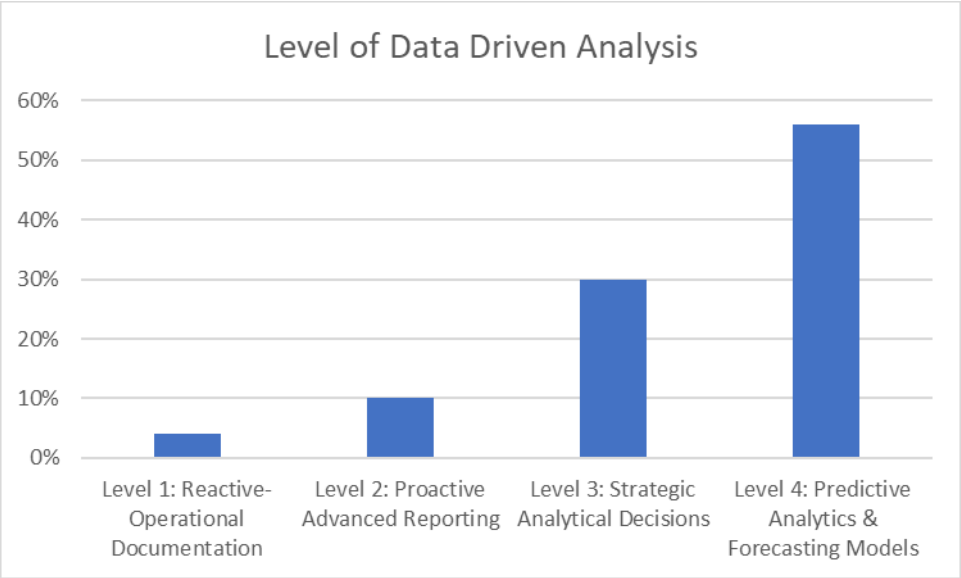


Figure 8. Level of data analysis used in different tiers of organisation

The results highlighted, defines the following conclusion that the Organisation of Level 3 & Level 4 that use Strategic Decision-making process & Predictive Forecasting analytical models for achieving their organisational objectives identifies a better & matured data driven functions, which is directly proportional to the increase in productivity & efficiency of the given organisation. According to the financial perspective, the stock price of these organisations that adopted Analytics in their operational domains had a relative higher value with respect to the fortune 500 companies.

Furthermore, In Human Resource Management, the organisations had a better reward & benefits structure, with improved retention rate, efficient talent acquisition & notable effectiveness in leadership. Therefore, becoming thrice as cost effective & productive within their competitive sector.

Thus, Statistical models defines an efficient potential with low investment, which is used to reinforce & forge an effective competitive advantage.

Human Resource Analytics for Human resource capital & resource management uses Human Resource Systems. HR Systems can be defined as the information technology architecture that stores, evaluate & analyses the data that is classified into Human resource metrics, & thereby falls under the classification of Payroll Management, Compensation management, Recruitment, Training management, Insurance, Performance management, Cultural Change management, policies & reforms, Survey Analytics, Feedback management, Benefit Analysis etc.

Professor Huselid defined a framework for workforce identification & differentiation which was directly proportional to organisational strategies, defined through the matrix of differentiated impact against the appropriate fit within the organisation. The matrix was further classified into 4 stage structure for the organisation:

Stage 1- Similar Concept: Strategy is aligned to external practices carried out by other organisation with a tried & tested avenue.

Stage 2- Generic: Different HR & Workforce Strategies for different Corporate Strategies.

Stage 3- Differentiation: HR & Workforce is integrated to corporate strategies with respect to the talent requirements for the strategic objectives.

Stage 4- Differentiate-Jobs: Workforce & Human resource capital is allocated based upon the nature of the job present within the strategic objective.

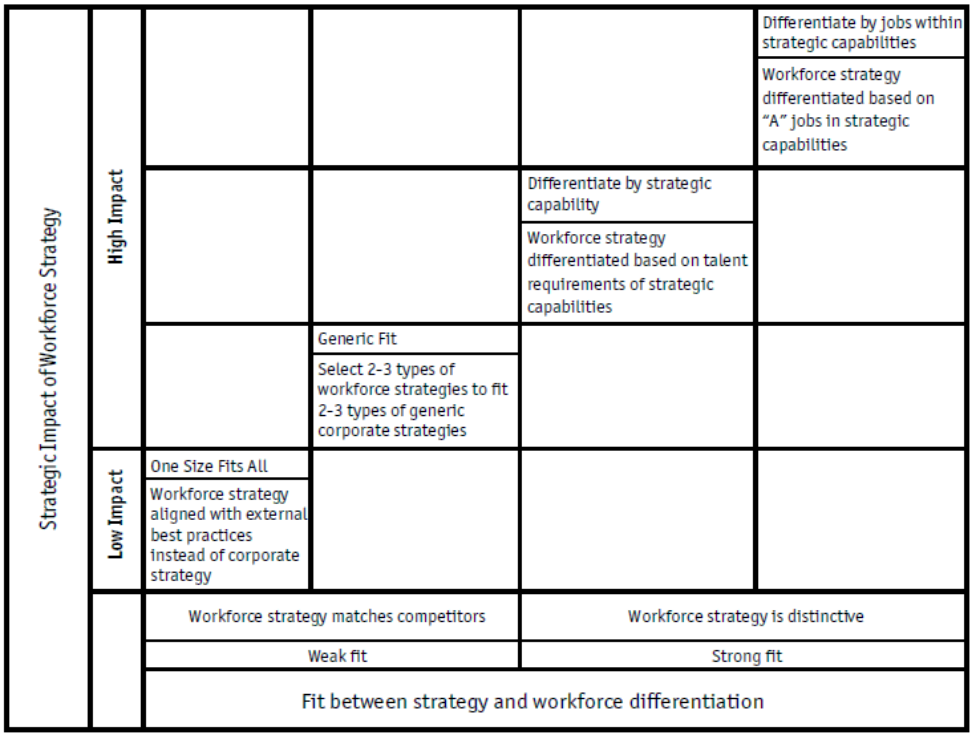


Figure 9. Workforce Strategy- Mark Huselid

However, the research can impose challenges for the Human Resource Executives, as they're quantifying an employee or worker, which imposes ethical bias within the organisation. Thus, HR Metrics are still under development to provide a standardised measurement system with respect to the industry/sector.

According to researchers, such as Wayne Cascio (Professor of Management, University of Colorado) & John Boudreau (Professor of Management, Marshall School of Business) developed a model or framework for Human resource measurement for an organisation into 4 components, which are referred to as:

L- Logic: Statement that creates a relationship between numbers & outcomes.

A- Analytics: Conclusion derived from the analysis of the variables & key factors.

M- Measures: Quantification of data.

P- Process: Creating nodes of objectives to establish a strategy based upon analysis.

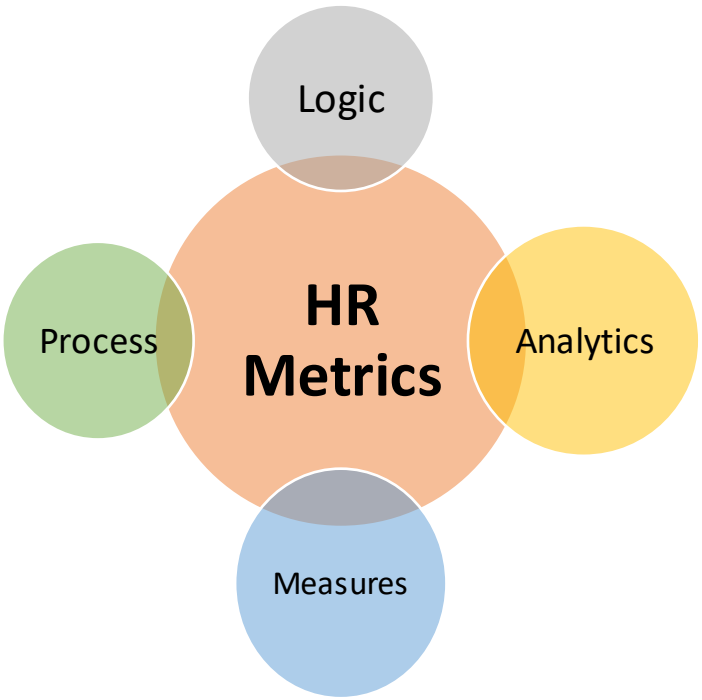


Figure 10. LAMP Framework

According to the LAMP Framework,

Logic: Clear & defined structure for logical relationship should be established between the measured and the expected output values. The logic characteristic of measurement identifies & classifies the variables and their effect over the given output.

Analytics: Conclusion is derived from the variables & the relationships identified from logic measurement. Sound & Clear analysis is the core of research for HR Analytics & Human resource metrics. In the respective step, causation between factors is eclipsed to avoid linear correlation within the data structure.

Measures: Characteristics of measurement should be- Periodic, Consistent, Complete, & Reliable. The database management system is the core component of "Measures" in the respective LAMP Framework.

Process: The process is used to devise & derive strategic objectives from the data & relationships classified in the previous steps. Process can also be used to evaluate relationships & create generic HR Metrics based upon the requirements of the organisation.

Strategic Human Resource Management has morphed into a segment of an organisation that has shareholdings in the strategic decisions & organisational objectives rather than simply carrying out the traditional prerequisite activities (Recruitment, Rewards & Compensation etc). Human resource management has become extremely efficient in terms with administrative objectives through the use of HR Analytics, Workforce analytics, & people analytics.

The impact caused by the development of HR Analytics is parallel to the development of knowledge-based economy. Evidently, HR Management adds a significant value to the gross productivity & efficiency of the organisation.

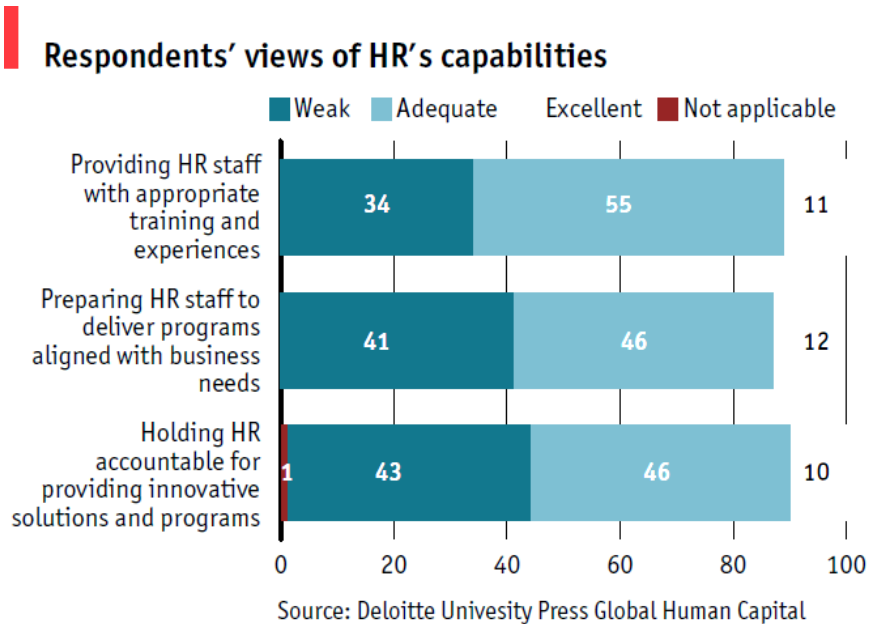


Figure 11. Respondent's view of HR

However, Executives don't prefer Human Resource teams for analytical problems & issues, as the traditional view of HR is based upon simply the corresponding traditional activities such as recruitment, settlements, compensation management, & benefit analysis or labour relations. Thus, executives use Human Resource department as a Commodity rather than an Asset.

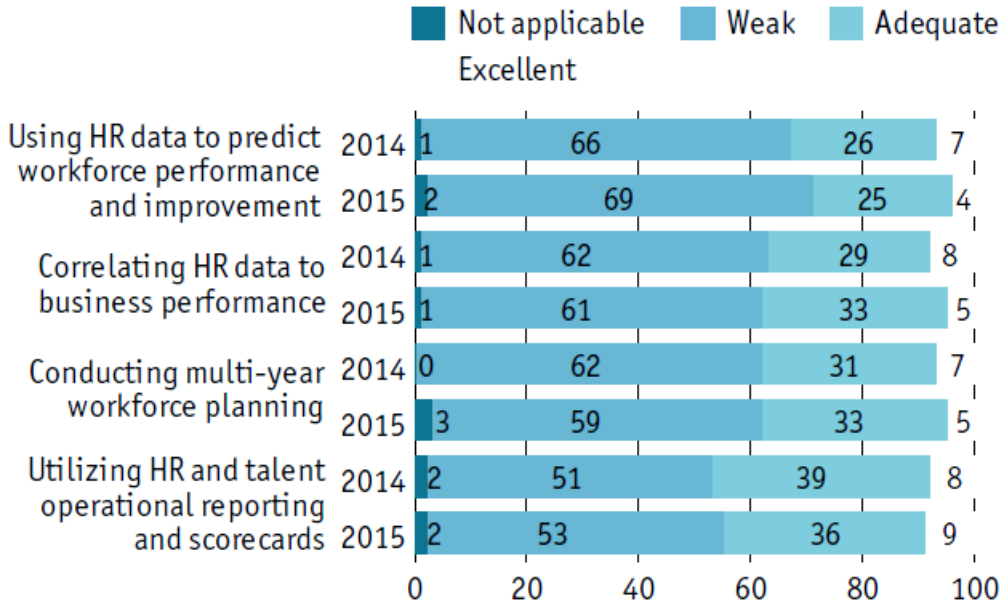


Figure 12. Use of HR Data

Analysis of Reactive Analytics & Predictive Analytics in Human Resource Management,

Tata Consultancy Services Survey (2014), identifies that the major component of Human Resource domain that affects the efficiency of an organisation is Attrition & Retention, followed by effectiveness of employee, talent acquisition, compensation management, reward analysis etc.

Use of predictive analytics is used by at least 40% of the total organisation in order to ascertain generalised future outcomes identified through statistical modelling with respect to the historical performance & data defined in the organisational archives, which is used to establish Organisational strategies & Corporate objectives to achieve their respective Vision.

Human Resource Capital management showed an effective increase of 8% i.e., from 15% to 23%, in the use of insightful analytical decisions which led to increase in productivity of the respective firm.

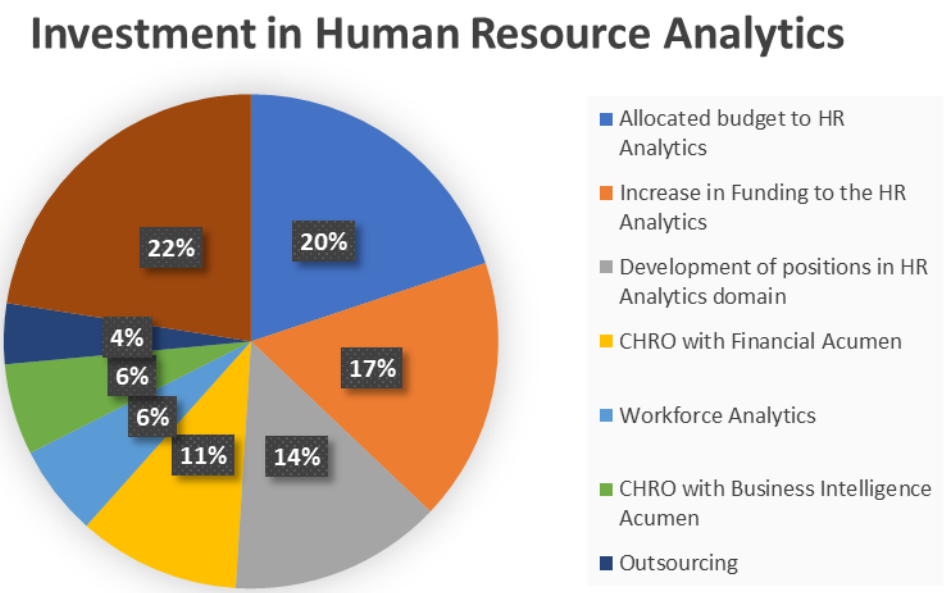


Figure 13. Investment in Human Resource department

Defined results show that there will be technological revolution within the corporate ecosystem, that allows the organisation to base their decision making process over analytical simulations formed over the foundations of Big Data. The tectonic shift, will change the Anatomy & structure of the Organisational behaviour along with its domains, which will be forced to evolve with the data driven-knowledge economy.

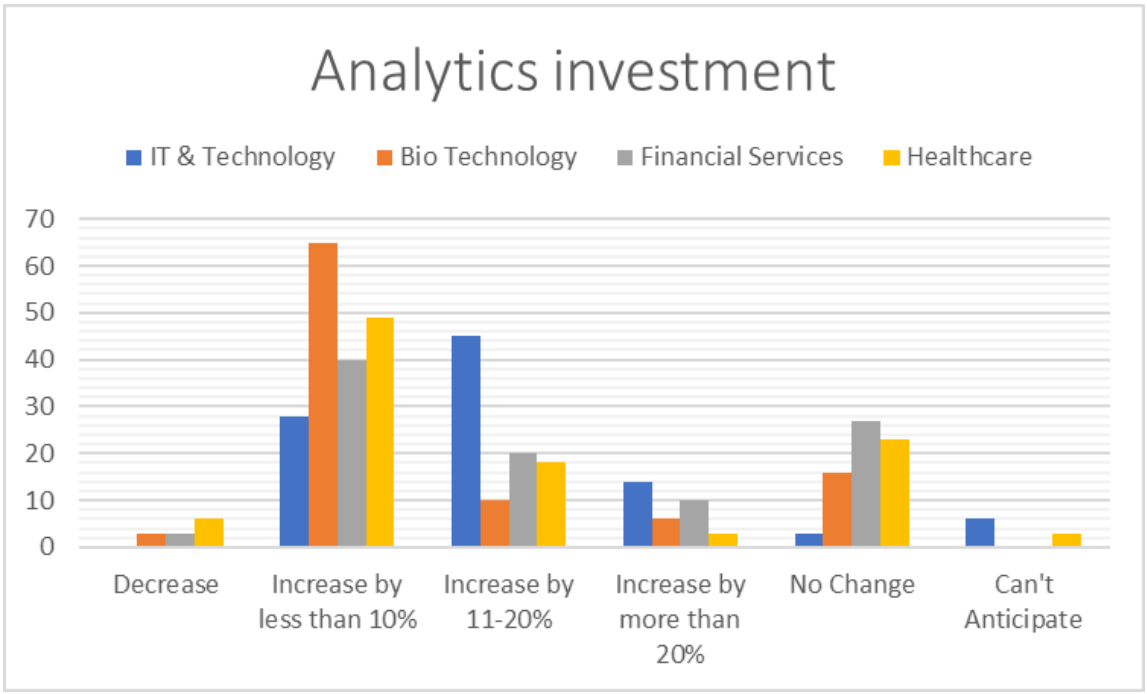


Figure 14. Investment in different Industries

Chapter 3

3. Research & Concepts

3.1. HR Metrics

HR Metrics can be defined as the indicators that are used by organisations & corporations in order to track the effectiveness of their organisational strategies, policies & strategic objectives across the different domains of corporate structure- Marketing, Finance, Human Resource, Sales, IT & Technology, and Operations etc.

HR Metrics are periodically defined across teams & departments to identify the need of initiatives & the area of improvements within the organisation in order to improve the gross efficiency & productivity. They vary across sectors as well as organisation.

HR Management

Percentage of HR Staff in Professional and/or Technical Roles This is very useful, especially for issues such as budgeting in regards to FLSA. Generally positions are exempt, only allowing straight time for overtime if allocated. If overtime is warranted, this would need to be assessed for the year's budget. Positions in this category may be called recruiter, benefits administrator, HR generalist, etc.	**Formula** Number of HR staff in professional technical positions ÷ the total number of HR staff
Percentage of HR Staff in Administrative Support Roles Often, but not always, positions in this category are non-exempt. They may be called coordinator, assistant, etc.	**Formula** Number of HR staff in administrative support positions ÷ by the total HR staff
HR Expenses Human resource expenses represent HR's total costs for a given fiscal year.	**Formula** No further computations are required beyond what is listed for the completion of this metric.
HR Expense to Operating Expense Ratio This ratio depicts the amount of HR expenses as a percentage of total operating expenses, which is an indication of the proportion of dollars an organization invests in its HR function.	**Formula** Total HR expenses ÷ total operating expenses
HR Expense per FTE/FTW HR expense by FTE/ FTW ratio represents the amount of human resource dollars spent per FTE or FTW in the organization. FTWs include employees and non-employee workers (temps, contractors, interims) supported by HR.	**Formula** HR expenses/ Total number of FTEs or FTWs

HR Expense to Revenue Ratio This information is useful for fiscal budgeting. To have this for each fiscal year creates a standard for projected budgeting costs for each year on HR expenses. HR Expenses should include outsourcing expenses.	**Formula** Total HR Expenses ÷ Revenue
Percentage of exceptions processed for payroll, benefits, promotions, and other HR This metric is helpful to understand the amount of special effort required to process benefits, promotions, and other HR transactions that are out of the standard protocol.	**Formula** Total number of exceptions processed by HR ÷ all HR transactions
HR-to-Employee/Worker Ratio The HR-to-Employee ratio and HR-to-Worker ratios provide a way to compare HR staffing levels across and within organizations. It represents the number of HR staff per 100 employees/workers supported by HR in the organization.	**Formula** (HR FTEs ÷ total number of FTEs in the organization) x 100 (HR FTEs / total number of workers supported by HR) x 100
Percentage of HR Staff in Supervisory Roles This is useful in determining span of control within HR.	**Formula** Number of HR staff in supervisory positions ÷ total number of HR staff

Financial Management

Total Human Capital (HC) $pend to Total Operating Spend Ratio Comparing total HC spend to the organization's total spend on all operating expenses, including human capital, shows the organization's relative prioritization regarding operational expense priorities and needs. Changes in this ratio can also show the relative changes in efficiency and productivity between operating expense areas, like IT, real estate, and human capital. It is also useful for budgeting purposes.	**Formula** Total HC Spend/ Total Operating Spend
Revenue Per FTE The Total Revenue divided by the number of FTEs. This ratio conceptually measures the efficiency and productive use of human capital because it links the time and effort associated with the firm's human capital to its revenue output. If the revenue-per-FTE ratio increases, it might indicate that more output is being produced per FTE. However, if it increases due primarily to major declines in FTEs from involuntary staff reductions or increased outsourcing, this may be misleading. The metric can temporarily look like increased efficiency or productivity. If revenue is not sustained over time with the lower staff levels then productivity and/or efficiency have not actually improved.	**Formula** Revenue ÷ number of FTEs
Earnings before investments and taxes (EBIT) per FTE EBIT per FTE is a better measure of the efficiency and productive use of human capital because it incorporates the operating costs involved in productivity improvements, like investments in IT. Increasing revenue, lowering expenses, reducing employees, and increasing worker productivity have a positive impact on this metric. This metric can be improved further if you use Total FTE's vs Employee FTEs since Total FTEs incorporates the productivity contributions of the contingent element of your workforce.	**Formula** EBIT ÷ number of FTEs

Revenue per Total Human Capital (HC) $pend	Formula
The total amount of revenue received during an organization's fiscal year divided by the total spend on Human Capital. This ratio conceptually links the costs associated with the firm's human capital to its productivity. If the revenue-per-THCS ratio increases, it indicates that there is greater efficiency and productivity because more output is being produced per $ spent on human capital. If the ratio decreases, it indicates there is less efficiency and productivity. Total Human Capital Spend should include wages, benefits; independent contractors, temps and other non-employee workers; and, HR program costs (non-staff) including outsourcing.	Revenue ÷ Total HC $pend

Staffing & Recruitment:

Contingent Representation Rate	Formula
Degree of contingent staff within your total workforce. Establishing targets for this metric monitoring it will tell you if you are complying with the contingent vs employee organization balance you have determined Is optimal for the accomplishment of organization goals and objectives, including human capital and operating expense targets.	(Contingent headcount FTEs/ Total Workforce FTEs) x 100
Time-to-Start Average number of days it took to fill a position. This metric typically includes positions filled by both external and internal hires. Starting with the day the position became available – which can be the date of resignation of the prior incumbent or the day the position received budget approval or simply when the hiring manager communicated that he/she was ready to fill the position - rather than when a requisition is received by HR, and ending with start date vs date filled, show a more organization vs HR focus; and, help show whether activities outside HR are helping or hindering efficient hiring. Sub-metrics within this metric which can be measured to help improve process elements include Time to Approval, Time to 1st Interview, Time to Offer, and Time to Fill. You should measure Time to Start for both External Hires and Internal Hires. You need agreement on whether you are counting calendar days or working days, and whether you minus days that recruiting is suspended.	**Formula** (Total days elapsed from the date each filled position was available to the date each new person started in the position) / Number of positions filled
Time-to-Productivity Average number of days to satisfactory productivity. This metric typically includes positions filled by both external and internal hires. You need agreement on whether you are counting calendar days or working days, and whether you minus days that recruiting is suspended. Organizations are finding unique and simple ways to identify the date of minimal acceptable productivity from using manager self-service reporting to very brief surveys (often just one question) that are set to automatically check in with hiring managers weekly until they receive a positive response. This metric is crucial since it reflects the organization's need for productivity vs just having a person in the job. Outcomes with this metric can reflect on the quality of your recruitment, selection, onboarding, and management of new employees.	**Formula** (Total days elapsed from the date each filled position was available to the date each new person achieved satisfactory productivity) / Number of positions filled

Turnover Rate	Formula
Rate at which employees are leaving the organization in a given time period. It is suggested that Turnover be categorized as Employer Intended vs Employer Unintended, and the latter category be further divided into Voluntary and All Others. The objective of measuring turnover is to determine where and when the organization has risk of losing talent that it doesn't want to lose, and to determine how to mitigate that risk. Therefore identifying Employer Intended separations segments out of that risk analysis terminations for poor performance or cause, layoffs or job eliminations, acceptance of early retirement offers, etc. which are irrelevant to identifying and mitigating the risk. Identifying Voluntary (resignation and retirement) separately from other Employer Unintended, like death, incarceration, job abandonment, refusal to accept new assignment, etc. also helps to focus our risk analysis. The Voluntary category is the most relevant to the Turnover risk analysis. Turnover of New Hires and Failure to Start Rate are also good metrics for Staffing professionals to be measuring. Other Turnover subgroups are important to other areas of analysis and decision making. For example, Turnover of Poor Performers can provide insight into the effectiveness of your Performance Management. Turnover rates are also useful inputs into Workforce Planning. The reporting of overall turnover is no longer considered best practice. This metric is unlikely to inform and improve decision making. Focus on key employee populations: Top Performers, New Hires, Poor Performers, Successors, High Potentials, Key Positions, High Risk Employees. These are the groups worth acting on if Turnover becomes unacceptable.	(Number of separations during the time period ÷ average actual number of employees during the time period) x 100 Time periods – typically year, quarter, month, pay period
Cost of Turnover and Cost per Turnover The average direct monetary costs associated with a position that was vacant due to turnover and is refilled. Costs include separation pay, payables to temps and contractors, overtime pay to other employees to cover, and staffing costs for replacement hiring. It should be noted that this metric does not reflect significant non-direct costs like loss of revenue, damage to customer relationships, and temporary or long-term productivity and performance differentials.	**Formula** Total of the costs of separation + vacancy + replacement Turnover costs/ # of positions filled due to separation
Retention Degree to which an organization is retaining key employees. As an example, this can tell you what the retention rate of University Relations hires is at 1, 3, and 5 years of service and whether the rate is different for different Universities or for those that interned with your organization vs those that did not.	**Formula** # of employees in the selected group employed at the designated time/ # of employees in that selected group originally

Turnover Impact and Impact per Employer Unintended Separation Total and Average Experience Lost due to Employer Unintended turnover.	**Formula** Total years of experience of all Employer Unintended separations Turnover Impact/ Number of Employer Unintended separations
Cost Per Hire Average cost incurred with an external hire. Total costs should include the sum of all direct costs (e.g., advertising, hiring events, agencies, search firms, employee referral programs, onboarding and travel for applicants and interviewers) incurred in attracting and hiring employees. Some organizations also include relocation costs, interviewer pay, and staffing department operating expenses. If the HR interviewers have other responsibilities like internal hiring or generalist duties then pay would need to be pro-rated for the time involved in external recruiting. If you include management interviewers you would also need to pro-rate pay since they have many other duties.	**Formula** Total costs related to all external hires/ Number of external hires
Vacancy Costs and Cost per Vacancy Total and average direct costs resulting from vacant positions. It should be noted that this metric does not reflect significant non-direct costs like loss of revenue, damage to customer relationships, and temporary or long-term productivity and performance differentials.	**Formula** (Total of the costs of temporary workers + independent contractors + temporary outsourcing + overtime) - wages and benefits not paid to vacant positions Vacancy Costs/ # of vacant positions
Vacancy/Occupancy Rate Measures the percentage of approved positions that is unfilled or filled at a given time. Positions may be vacant due to turnover or because they are new and have never been filled. These measures are particularly important for key positions, e.g., strategic jobs, time consuming and expensive to fill jobs, critical project staff.	**Formula** (Total number of vacant or occupied positions ÷ total number of approved positions) x 100

Development

Competency Rate Degree to which employees in key positions have the competencies necessary to achieve their performance objectives.	**Formula** (# of incumbents with competency ratings of Acceptable or better/ # of incumbents who have received competency assessments) x 100

Training:

Training Participation Rate Percentage of employees who participated in company paid training.	**Formula** (Number of employees who participated in at least one company paid training activity/ Number of employees eligible for training) x 100
Training Spend Rates Relative importance of spend on training vs other operating and human capital activities. The importance is derived by comparing these metrics to your unique targets since various circumstances drive what is optimal for any one organization.	**Formula** (Training spend/ Total Human Capital Spend) x 100 (Training spend/ Total Operating Spend) x 100
Average Training Spend The monetary investment in training at an individual level. The expenses should include all direct training costs: e.g., materials, trainer, associated travel, logistics.	**Formula** Training spend ÷ Number of workers participating in training
Average Training Hours The time investment in training at an individual level.	**Formula** Total training hours ÷ total number of workers participating in training
Required Training Completion Rate Shows compliance with training requirements. It is also useful for budget and resource planning.	**Formula** (Total number of workers who have completed a specific required training ÷ total number of workers who are required to take that training) x 100

Performance:

Performance Review Completion Rate Percentage of completed reviews	**Formula** (Number of completed performance reviews/ Number of completed performance reviews due) x 100
Average Performance Rating The mean performance rating across a selected group of employees receiving performance assessments.	**Formula** (Total of all Performance Ratings/ Number of employees who received a Performance Rating) x 100
Performance Rating Distribution The employee representation across each of the available Performance Ratings. This distribution can provide insight into the degree of use of the full scale, suggest possible rating inflation, illustrate where there are issues with under performance, and reveal any variance with organization distribution targets.	**Formula** (Number of employees who received each rating/ Number of employees who received a Performance Rating) x 100

3.2. Tools & Techniques

The collected data was classified and tabulated in MS-Excel for analysis and interpretation. The graphical representation is done using MS-Excel, Power BI and a statistical test was carried out using SPSS software.

3.3. Case Study 1: HR Metrics

Cost Information

External hire Costs		
1	Newspaper Ad Cost	1,50,000
2	Agency Fee	600000
3	Total referral bonus	180000
4	Web job board fee	250000

External hire (cost per employee)		
1	Background check	5000
2	Medical check-up	3000
3	Travel cost	25000
4	Processing cost	10000

Internal hire cost		
1	IJP Ad Cost	25000

Internal hire (cost per employee)		
1	Travel cost	25000
2	Processing cost	2000

Table 3- Case 1

Employee Information

Sample Size: 44

Total Hires = 44

Total External Hire = 36

Total Internal Hire = 8

Total Internal Cost of Hire	Fixed Internal Cost + No. of Internal Hires (Variable Internal Cost)
	241000

Total External Cost of Hire	Sum of all the Fixed Cost + No. of External Hires (Sum of External Hire Cost)
	2728000

Total Cost of Hire	Sum of Total External Cost + Total Internal Cost
	2969000

Cost of Hire	67477.27	***Total Cost on hiring process/ Total No. of Employees***
Cost of External Hire	75777.78	***Total Cost of External Hire/ Total External Hires***
Cost of Internal Hire	30125	***Total Cost of Internal Hires/ Total Internal Hires***

Therefore, for every internal hire, the organisation is **Saving** = (Cost of External hire – Cost of Internal hire) = **45652**

3.4. Tables & Information

Table 3-Case 1:
The following data is extracted from Kaggle for the purpose of development of HR Dashboards.

Data Source:
https://www.kaggle.com/HRAnalyticRepository/employee-attrition-data,

https://rpubs.com/rhuebner/hrd_cb_v14

Table 3- Case 1

Sr. No.	Employee Name	Employee Numbe	Sta	Zip	DOB	Ag	Sex	MaritalDes	CitizenDesc	Date of Hi	Department	Position	Pay Ra	Manager Name	Employee Source	Performance Score
1	Brown, Mia	1103024456	MA	1450	11/24/1985	32	Female	Married	US Citizen	10/27/2008	Admin Offices	Accountant I	28.5	Brandon R. LeBlanc	Internal	Fully Meets
2	LaRotonda, William	1106026572	MA	1460	4/26/1984	33	Male	Divorced	US Citizen	01-06-2014	Admin Offices	Accountant I	23	Brandon R. LeBlanc	Website Banner Ads	Fully Meets
3	Steans, Tyrone	1302053333	MA	2703	09-01-1986	31	Male	Single	US Citizen	9/29/2014	Admin Offices	Accountant I	29	Brandon R. LeBlanc	Internet Search	Fully Meets
4	Howard, Estelle	1211050782	MA	2170	9/16/1985	32	Female	Married	US Citizen	2/16/2015	Admin Offices	Administrative Assistant	21.5	Brandon R. LeBlanc	Pay Per Click - Google	N/A- too early to review
5	Singh, Nan	1307059817	MA	2330	5/19/1988	29	Female	Single	US Citizen	05-01-2015	Admin Offices	Administrative Assistant	16.56	Brandon R. LeBlanc	Website Banner Ads	N/A- too early to review
6	Smith, Leigh Ann	711007713	MA	1844	6/14/1987	30	Female	Married	US Citizen	9/26/2011	Admin Offices	Administrative Assistant	20.5	Brandon R. LeBlanc	Internal	Fully Meets
7	LeBlanc, Brandon R	1102024115	MA	1460	06-10-1984	33	Male	Married	US Citizen	01-05-2016	Admin Offices	Shared Services Manager	55	Janet King	Monster.com	Fully Meets
8	Quinn, Sean	1206043417	MA	2045	11-06-1984	33	Male	Married	Eligible NonCitizen	2/21/2011	Admin Offices	Shared Services Manager	55	Janet King	Internal	Fully Meets
9	Boutwell, Bonalyn	1307060188	MA	2468	04-04-1987	30	Female	Married	US Citizen	2/16/2015	Admin Offices	Sr. Accountant	34.95	Brandon R. LeBlanc	Internal	90-day meets
10	Foster-Baker, Amy	1201031308	MA	2050	4/16/1979	38	Female	Married	US Citizen	01-05-2009	Admin Offices	Sr. Accountant	34.95	Board of Directors	Other	Fully Meets
11	King, Janet	1001495124	MA	1902	9/21/1954	63	Female	Married	US Citizen	07-02-2012	Executive Office	President & CEO	80	Board of Directors	Pay Per Click - Google	Fully Meets
12	Zamora, Jennifer	1112030816	MA	2067	8/30/1979	38	Female	Single	US Citizen	04-10-2010	IT/IS	CIO	65	Janet King	Employee Referral	Exceptional
13	Becker, Renee	1102024056	MA	2026	04-04-1986	31	Female	Single	US Citizen	07-07-2014	IT/IS	Database Administrator	43	Simon Roup	Search Engine - Google Bing Yahoo	Fully Meets
14	Goble, Taisha	905013738	MA	2127	10/23/1971	46	Female	Single	US Citizen	2/16/2015	IT/IS	Database Administrator	48.5	Simon Roup	Glassdoor	Fully Meets
15	Hernandez, Daniff	1410071156	MA	1960	08-07-1986	31	Male	Married	US Citizen	2/16/2015	IT/IS	Database Administrator	40.1	Simon Roup	Employee Referral	N/A- too early to review
16	Horton, Jayne	1105025718	MA	2493	2/21/1984	33	Female	Single	US Citizen	3/30/2015	IT/IS	Database Administrator	34	Simon Roup	Glassdoor	N/A- too early to review
17	Johnson, Noelle	1003018246	MA	2301	11-07-1986	31	Female	Married	US Citizen	01-05-2015	IT/IS	Database Administrator	40	Simon Roup	Glassdoor	90-day meets
18	Murray, Thomas	1406068403	TX	78230	07-04-1988	29	Male	Divorced	US Citizen	11-10-2014	IT/IS	Database Administrator	35.5	Simon Roup	Internal	Exceptional
19	Pearson, Randall	1102023965	MA	2747	09-05-1984	33	Male	Married	US Citizen	12-01-2014	IT/IS	Database Administrator	41	Simon Roup	Employee Referral	Fully Meets
20	Petrowsky, Thelma	1108027853	MA	1886	9/16/1984	33	Female	Married	US Citizen	11-10-2014	IT/IS	Database Administrator	42.75	Simon Roup	Employee Referral	Exceptional
21	Roby, Lori	1407068885	MA	1886	10-11-1981	36	Female	Married	US Citizen	2/16/2015	IT/IS	Database Administrator	39.55	Simon Roup	Employee Referral	Fully Meets
22	Rogers, Ivan	1203032255	MA	1810	8/26/1986	31	Male	Married	US Citizen	3/30/2015	IT/IS	Database Administrator	42.2	Simon Roup	Pay Per Click - Google	N/A- too early to review
23	Salter, Jason	1111030148	MA	2452	12/17/1987	30	Male	Divorced	US Citizen	01-05-2015	IT/IS	Database Administrator	45	Simon Roup	Vendor Referral	90-day meets
24	Simard, Kramer	808010278	MA	2110	02-08-1970	47	Male	Married	US Citizen	01-05-2015	IT/IS	Database Administrator	30.2	Simon Roup	Employee Referral	90-day meets
25	Zhou, Julia	1110029732	MA	2148	2/24/1979	38	Female	Single	US Citizen	3/30/2015	IT/IS	Database Administrator	31.4	Simon Roup	Employee Referral	90-day meets
26	Foss, Jason	1192991000	MA	1460	07-05-1980	37	Male	Single	US Citizen	4/15/2011	IT/IS	IT Director	65	Jennifer Zamora	Professional Society	Exceptional
27	Roup,Simon	1106026933	MA	2481	04-05-1973	44	Male	Single	US Citizen	1/20/2013	IT/IS	IT Manager - DB	62	Jennifer Zamora	Professional Society	Fully Meets
28	Ruiz, Ricardo	1001175250	MA	1915	01-04-1964	54	Male	Divorced	US Citizen	01-09-2012	IT/IS	IT Manager - DB	21	Jennifer Zamora	Internal	Fully Meets
29	Monroe, Peter	1011022863	MA	2134	10-05-1986	31	Male	Married	Eligible NonCitizen	2/15/2012	IT/IS	IT Manager - Infra	63	Jennifer Zamora	Internal	Needs Improvement
30	Dougall, Eric	1101023754	MA	1886	07-09-1970	47	Male	Single	US Citizen	01-05-2014	IT/IS	IT Manager - Support	64	Jennifer Zamora	Professional Society	Exceeds
31	Clayton, Rick	1301052902	MA	2170	09-05-1985	32	Male	Single	US Citizen	09-05-2012	IT/IS	IT Support	28.99	Eric Dougall	Glassdoor	Fully Meets
32	Galia, Lisa	1501072093	CT	6040	07-06-1968	49	Female	Single	US Citizen	05-01-2010	IT/IS	IT Support	31.4	Eric Dougall	Vendor Referral	Fully Meets
33	Lindsay, Leonara	602000312	CT	6070	10-05-1988	29	Female	Single	US Citizen	1/21/2011	IT/IS	IT Support	26	Eric Dougall	Internal	Exceeds
34	Soto, Julia	1203032263	MA	2360	03-12-1973	44	Female	Married	US Citizen	06-10-2011	IT/IS	IT Support	27.49	Eric Dougall	Information Session	Fully Meets
35	Bacong, Alejandro	1212052023	MA	1886	01-07-1988	30	Male	Divorced	US Citizen	01-05-2015	IT/IS	Network Engineer	45	Peter Monroe	Glassdoor	90-day meets
36	Cisco, Anthony	1102024173	MA	2135	11/24/1989	28	Male	Married	US Citizen	3/30/2015	IT/IS	Network Engineer	42	Peter Monroe	Information Session	N/A- too early to review
37	Dolan, Linda	1101023540	MA	2119	7/18/1988	29	Female	Married	US Citizen	01-05-2015	IT/IS	Network Engineer	37	Peter Monroe	Employee Referral	90-day meets
38	Gonzalez, Maria	1988299991	MA	2472	4/16/1981	36	Female	Separated	US Citizen	01-05-2015	IT/IS	Network Engineer	39	Peter Monroe	Employee Referral	Fully Meets
39	Merlos, Carlos	1012023013	MA	2136	6/18/1987	30	Male	Single	US Citizen	3/30/2015	IT/IS	Network Engineer	43	Peter Monroe	Vendor Referral	N/A- too early to review
40	Monway, Tanya	1001956578	MA	2048	04-04-1979	38	Female	Married	US Citizen	2/16/2015	IT/IS	Network Engineer	27	Peter Monroe	Monster.com	Fully Meets
41	Shepard, Anita	906014183	MA	1773	4/14/1981	36	Female	Married	US Citizen	9/30/2014	IT/IS	Network Engineer	47	Peter Monroe	Vendor Referral	Fully Meets
42	Tredinnick, Neville	1104025466	MA	1420	05-05-1988	29	Male	Married	US Citizen	01-05-2015	IT/IS	Network Engineer	28	Peter Monroe	Monster.com	Fully Meets
43	Turpin, Jumil	1411071506	MA	2343	3/31/1969	48	Male	Married	Eligible NonCitizen	3/30/2015	IT/IS	Network Engineer	49.1	Peter Monroe	Employee Referral	N/A- too early to review
44	Ait Sidi, Karthikeyan	1307060199	MA	2148	05-05-1975	42	Male	Married	US Citizen	3/30/2015	IT/IS	Sr. DBA	62	Simon Roup	Company Intranet - Partner	Fully Meets

3.5. HR Dashboards

From Table 3-Case 1

Hiring Source

Hiring Source	
Total External Hire	36
Total Internal Hire	8
Total Hire	44

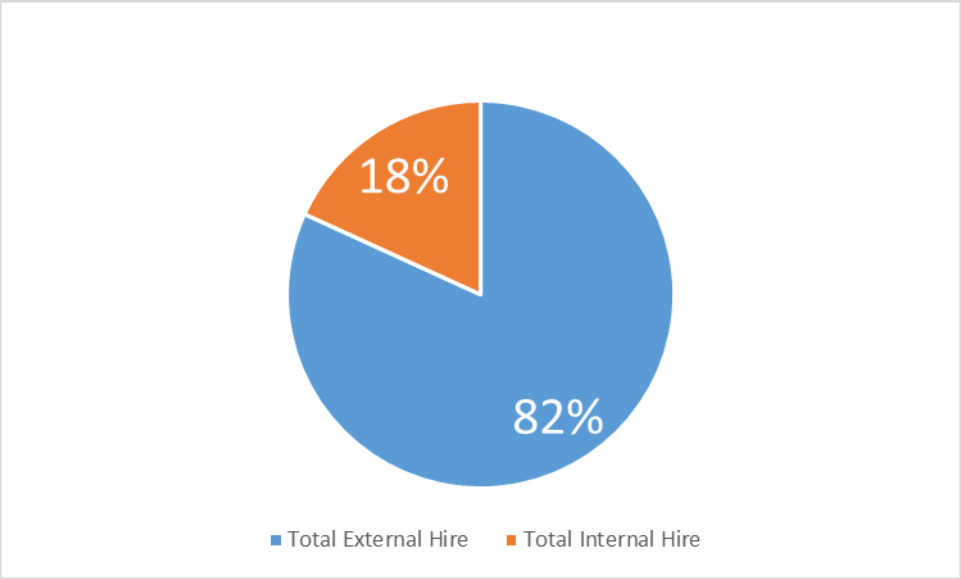


Figure 15. Analysis of Table 3-Case 1

Age Distribution

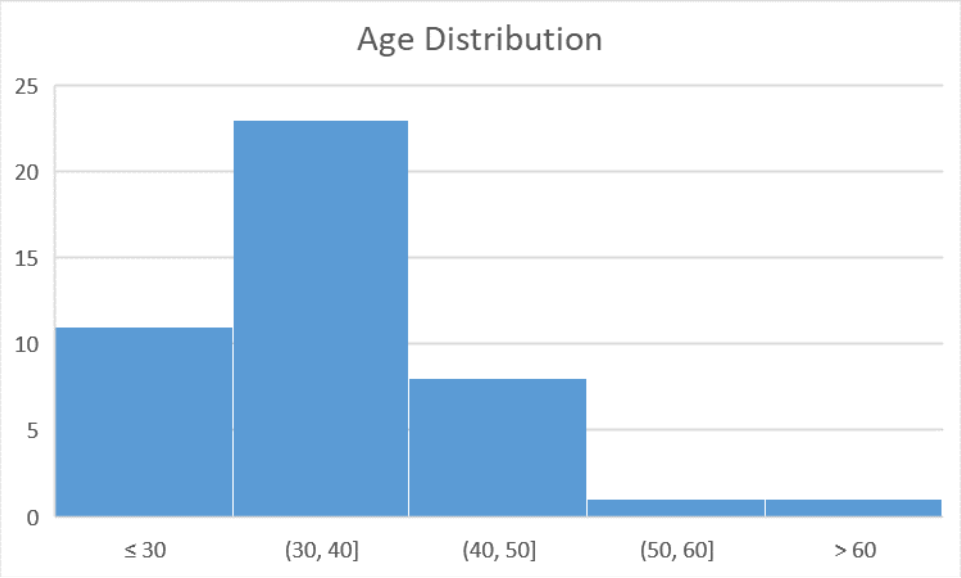


Figure 16. Analysis of Table 3-Case 1

Gender Distribution

Female	22
Male	22

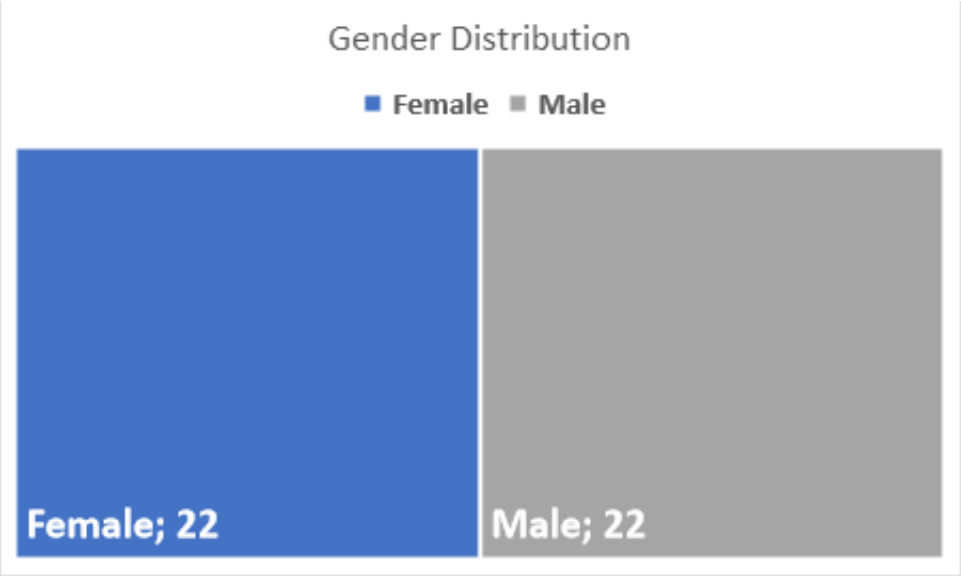


Figure 17. Analysis of Table 3-Case 1

Cost of Recruitment

Cost of Hire	67477.27
Cost of External Hire	75777.78
Cost of Internal Hire	30125

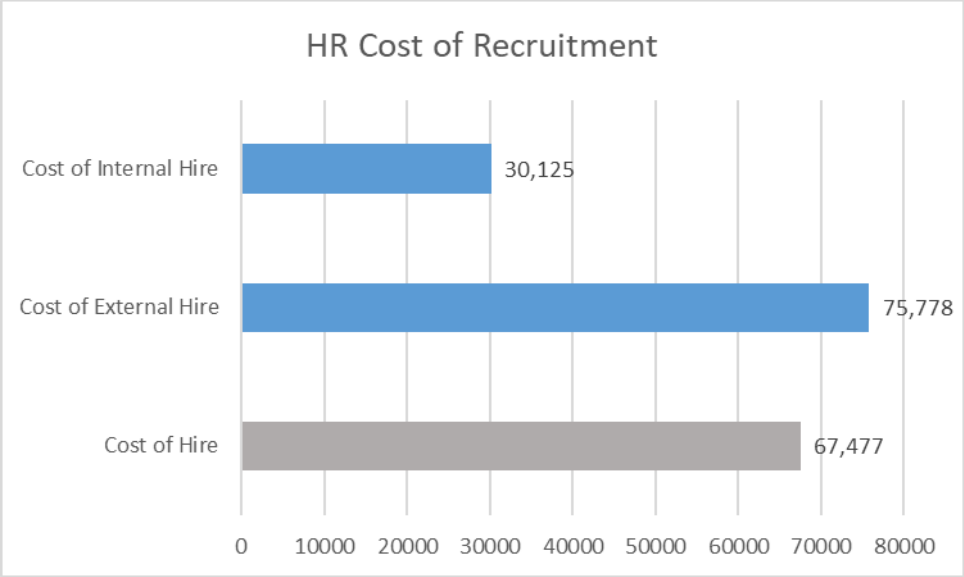


Figure 18. Analysis of Table 3-Case 1

Department wise Distribution

Row Labels	Count of Employee Number
Admin Offices	10
Executive Office	1
IT/IS	33
Grand Total	**44**

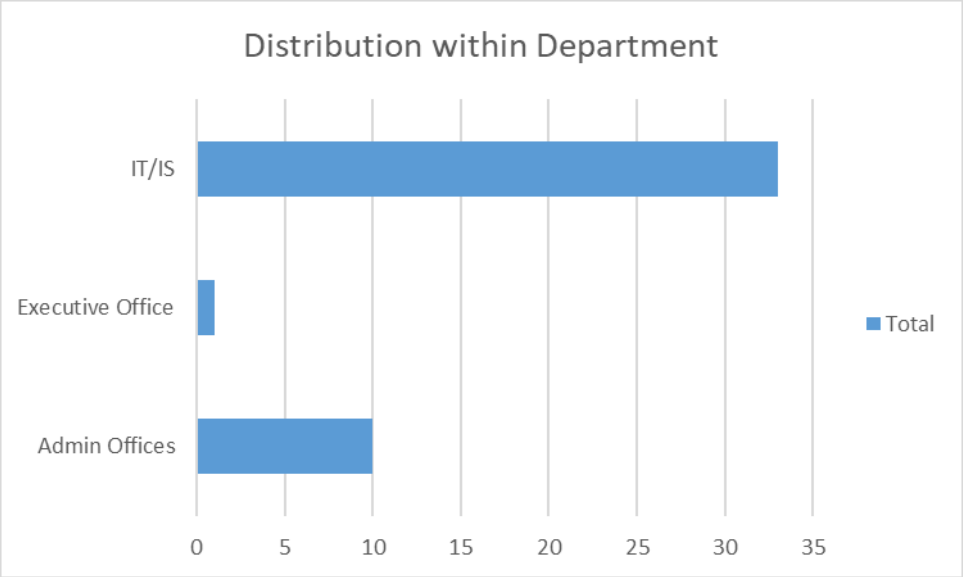


Figure 19. Analysis of Table 3-Case 1

3.6. Regression

Regression can be defined as the method that uses statistical model to establish & ascertain relationships between two or more variables through the means of quantifying association.

The respective methodology requires two types of variables-
Independent Variable/Cause Variable- Variables and factors that affect the magnitude of cause variable. They're essentially the reason of change and alterations defined by the analytical user, that leads to a change in certain output.

Dependent Variable/Effect Variable- The respective variable is dependent over the magnitude of effect variable. The following undergoes a change or alterations when the system of independent variable is disturbed.

$$Y_i = f(X_i, \beta) + e_i$$

Y_i = dependent variable
f = function
X_i = independent variable
β = unknown parameters
e_i = error terms

3.7. Prescriptive Analytics

Prescriptive Analytics can be defined as the trend identified through the use of predictive analysis & descriptive analysis. It provides a multitude of inferences, & thereby, provides an actionable output (defining the most effective solution) based upon the qualitative & quantitative research identified through the means of historical data.

The major feature of Prescriptive Analytics is the employment of "Optimisation" in the respective process for analytical reasoning.

3.8. Predictive Analytics

The Predictive Analytics uses historical information & classifies the information into continuous variables. The pre-processed data is then evaluated through the predictive analytical algorithm defined by the user.
Parameters in Predictive Analytics are:

- Historical Information
- Cause Variable
- Effect Variable
- Expected Output/Reference

Models can have the following roles:

i. **classification** – the target variable is discrete (i.e. decision trees, logistic regression),
ii. **approximation** – the target is continuous (i.e. linear regression, neural networks),
iii. **association** – co-occurrence of values (i.e. A-Priori algorithms, associative networks),
iv. **segmentation** – division into subgroups (i.e. k-means algorithm, Kohonen networks).

Chapter 4

4. Data Collection & Analysis

4.1. Data Collection & Analysis- Practical Application of the concept of regression in HR Analytics

ABB Services provides Consultation services within the domains for technology – Robotics, IT Services, Energy & Power, Oil & Gas, Automation etc. It's a global pioneer organisation that possess a dichotomy of portfolio.

Case 1: Mr. John Doe is an HR Analytics Manager at an International IT & Technology Consulting firm i.e., ABB Services. ABB hires multiple executives across different domains within their organisation for the Consultation Services. Thus, the Human Resource management team has to expend a lot of resources and time, in order to identify potential resumes for the respective profiles offered by the firm. Furthermore, the team is required to analyse individual CTC for the potential candidates.

Use of HR Analytics to measure & accomplish the general HR objectives for the potential candidates defined in the **Table 2- Case Study HR.**

The Analytical model uses the statistical model of multiple regression analysis to identify & predict the magnitude of the CTC to the potential candidates with respect to the historical data of previously hired employees through creating a relationship reference between dependent variable & independent variable, such as:

Table 2- Case Study

Sample Size: 1338 Employees

Characteristics/Variables identified from the historical data of employees (Manager & Executives) of the organisation ABB for the purpose of Talent Acquisition & Recruitment by the Human Resource Management Team were:

a. **College Category/College Type:** College Category has been classified into three categories – Tier 1, Tier 2, & Tier 3. The respective segregation was defined on the basis the nature & reputation of the college predefined in the academic domain. It highlights that the candidate has been to which degree of University/College for their post-graduation/graduation.

Row Labels	Count of S.No.
Tier 1	649
Tier 2	364
Tier 3	325
Grand Total	**1338**

b. **Roles/Designation:** Roles & Designation in the Table 2 provides the details of hierarchy the individual was hired at in the respective firm. It measures the level of authority for the prospective candidate. Furthermore, It is considered as one of the important features that directly affects the Cost to Company for an individual. The following case classifies the designation into two categories- Managers & Executives.

Row Labels	Count of S.No.
Executive	1064
Manager	274
Grand Total	**1338**

c. **Working Location:** Work location refers to the fixed specific region or area which the respective employee regularly pursues to follow their job within the terms of the organisation. It is classified into two categories- Metro & Non-Metro. The work location is classified on the basis of difference in urbanisation & culture in order to determine the general HR Analysis.

Row Labels	Count of S.No.
Metro	676
Non-Metro	662
Grand Total	**1338**

d. **Previous CTC:** Previous CTC or Cost to Company is the salary package amount given by the organisation to the employee that migrated to the organisation. Previous CTC is variable for different organisation as it is dependent upon the organisation's specific skill-set, performance management, organisation's policies & compensation management. Thus, the respective variable is numerical & independent in nature.

e. **Previous Job Change:** Previous job changes indicates the number of switches an individual has made before joining the respective organisation within a defined period of time (24 Months, in this case). It represents the catalogued numerical value that is associated with an individual representing the number of changes made within a particular period. The data represents that the maximum number of switches was 4, & minimum number of switches was 1, before the employee joined the respective organisation-ABB

Row Labels	Count of S.No.
1	333
2	313
3	348
4	344
Grand Total	**1338**

f. **Graduation Marks/Grades:** Graduation marks are the visual representation of the results or grades classified by the university/college through individual evaluation with respect to the marking schemes followed during their course. This is different & unique for every individual, as it is the cumulative percentage score defined by the university/college.

g. **Work Experience (Months):** It can be defined as the experience of the respective employee's consolidated into numerical component with respect to the summary of work/objectives through the periodic nodes of their corporate lifecycle, from initiation of their Job to the Exit. In this scenario, the data defines the work experience in terms of Months for every individual that was evaluate & hired within the organisation-ABB.

h. **CTC Offered/Cost to Company:** It is the aggregate annual package offered to an employee during the process of recruitment. It is the magnitude of compensation paid to the employee for the value that they define within the organisation. The Unit of CTC in the respective case is '$'. It defines the value that the organisation offered to the employee during the process of their recruitment. It is unique for every individual, as it is linked with the nature of multiple factors such as- education, experience, work location, previous CTC, Skill-set etc.

Problem Statement: Predict the CTC of a new employee/potential candidate based upon the historical data of the employees of the organisation through the means of statistical model defined through the variables or factors identified.

I. Identify the y-Variable or dependent variable

Y Variable will be the **"CTC"** component of the data defined in the **Table 2-Case Study**

Colleg	Role	City type	Previous CT(	Previous job changes	Graduation mark:	Exp (Months	CTC
Tier 1	Manager	Non-Metro	55,523.00	3	66	19	71,406.58
Tier 2	Executive	Metro	57,081.00	1	84	18	68,005.87
Tier 2	Executive	Metro	60,347.00	2	52	28	76,764.02
Tier 3	Executive	Metro	49,010.00	2	81	33	82,092.39
Tier 3	Executive	Metro	57,879.00	4	74	32	73,878.10
Tier 2	Executive	Non-Metro	54,340.00	4	73	31	59,950.89
Tier 2	Executive	Non-Metro	60,208.00	1	42	46	66,602.34

Figure 20. Snippet of Table 2 Case Study

As the CTC for the prospective candidate has to be calculated on the basis of the independent variables (x-variable), thus, CTC Component is the dependent variable whose value is regulated by the independent variable-x.

It is the "effect" of the influence identified by the independent variable.

II. Identify the x-Variable, or Independent Variable

X-Variables or Independent Variables will be classified into:

- College
- Role
- City Type
- Previous CTC
- Previous Job Changes
- Graduation Marks
- Experience (Months)

Colleg	Role	City type	Previous CT(	Previous job changes	Graduation mark:	Exp (Months	CTC
Tier 1	Manager	Non-Metro	55,523.00	3	66	19	71,406.58
Tier 2	Executive	Metro	57,081.00	1	84	18	68,005.87
Tier 2	Executive	Metro	60,347.00	2	52	28	76,764.02
Tier 3	Executive	Metro	49,010.00	2	81	33	82,092.39
Tier 3	Executive	Metro	57,879.00	4	74	32	73,878.10
Tier 2	Executive	Non-Metro	54,340.00	4	73	31	59,950.89

Figure 21. Snippet of Table 2 Case Study

III. Data Pre-processing:

Convert the Categorical Variable to Numerical or Continuous Variable in order to apply multiple linear regression to the respective data. Thus, the categorical variable identified in the given data are defined as,

Categorical Variables:

a. College

b. Role

c. City Type

a. **College-** It is classified into three categories, i.e., Tier 1, Tier 2, & Tier 3. Thus, two dummy variables will be created in order to translate the similar information into numerical values.

College_Tier1- 1st Dummy Variable- When the College is Tier 1, the data value will be equivalent to '1', or else it will carry the value '0' for Tier 2 & Tier 3.

College_Tier2- 2nd Dummy Variable- When the College is Tier 2, the data value will be equivalent to '1', or else it will carry the value '0' for Tier 1 & Tier 3.

If the College is neither Tier 1 nor Tier 2, then the College is Tier 3.

S.No.	College	College_T1	College_T2	
1	Tier 1	1	0	
2	Tier 2	0	1	
3	Tier 2	0	1	
4	Tier 3	0	0	
5	Tier 3	0	0	
6	Tier 2	0	1	

Figure 22. Data pre-processing-Table 2

b. **Role-** It is classified into two categories, i.e., Manager, & Executives.
Thus, single dummy variable is required to identify, if the individual belongs to a certain category.
Role_Manager- 1st Dummy Variable- The Individual selected is a Manager, therefore, it will hold the value of '1'.
If the individual is not a Manager, then they're classified as 'Executives', thus, the value will be equivalent to '0'.

Role	Role_Manager
Manager	1
Executive	0
Executive	0
Executive	0
Executive	0
Executive	0

Figure 23. Data pre-processing-Table 2

c. **City Type-** It is classified into two types, i.e., Metro & Non-Metro.
Thus, Single dummy Variable is required to identify, if the individual possess a Metro location.
City_Metro- 1st Dummy Variable- The Individual selected resides in a Metro City, & therefore, the data value will be equivalent to '1'.
Whereas, If the individual does not fall in the category of 'Metro', then they're considered under the category of 'Non-Metro', & will carry the value of '0'.

City type	City_Metro
Non-Metr	0
Metro	1
Metro	1
Metro	1
Metro	1
Non-Metr	0
Non-Metr	0

Figure 24. Data pre-processing-Table 2

Data After Pre-Processing:

Table 2-Case Study

S.No.	College	College_T1	College_T2	Role	Role_Manager	City type	City_Metro	Previous CT(	Previous j	Graduatio	Exp (Mont	CTC
1	Tier 1	1	0	Manager	1	Non-Metr	0	55,523.00	3	66	19	71,406.58
2	Tier 2	0	1	Executive	0	Metro	1	57,081.00	1	84	18	68,005.87
3	Tier 2	0	1	Executive	0	Metro	1	60,347.00	2	52	28	76,764.02
4	Tier 3	0	0	Executive	0	Metro	1	49,010.00	2	81	33	82,092.39
5	Tier 3	0	0	Executive	0	Metro	1	57,879.00	4	74	32	73,878.10
6	Tier 2	0	1	Executive	0	Non-Metr	0	54,340.00	4	73	31	59,950.89
7	Tier 2	0	1	Executive	0	Non-Metr	0	60,298.00	1	42	46	66,602.34
8	Tier 3	0	0	Executive	0	Non-Metr	0	49,944.00	2	56	37	57,768.44
9	Tier 1	1	0	Executive	0	Metro	1	53,124.00	4	40	37	70,083.30
10	Tier 3	0	0	Executive	0	Non-Metr	0	51,141.00	1	47	60	85,648.48
11	Tier 1	1	0	Executive	0	Metro	1	49,497.00	1	50	25	74,914.15
12	Tier 2	0	1	Manager	1	Non-Metr	0	50,197.00	2	66	62	85,219.39
13	Tier 1	1	0	Executive	0	Metro	1	63,234.00	4	73	23	82,910.94
14	Tier 2	0	1	Executive	0	Non-Metr	0	60,059.00	2	71	56	74,350.08
15	Tier 2	0	1	Manager	1	Metro	1	66,487.00	1	50	27	1,03,595.83

Thus, after conversion of categorical data into numerical data, the statistical model for analysis of relationship between Cost to company offered with respect to the Independent Variables (X-Variables) can be applied over the respective table, & thereby, resulting in the evaluation of magnitudes effects & cause between the dependent & independent variable.

IV. Create a Regression Model

Regression Statistics Table

Regression Statistics	
Multiple R	0.779863652
R Square	0.608187316
Adjusted R Squ	0.605828775
Standard Error	7880.077448
Observations	1338

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	8	1.28099E+11	1.6E+10	257.8658681	4.4389E-264
Residual	1329	82525079767	62095621		
Total	1337	2.10624E+11			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	32438.76192	2166.322566	14.97411	5.83E-47	28188.97735	36688.54649	28188.97735	36688.54649
College_T1	4659.731658	537.5128706	8.669061	1.24675E-17	3605.265468	5714.197848	3605.265468	5714.197848
College_T2	-832.2746616	619.1275007	-1.34427	0.179090432	-2046.8484	382.2990772	-2046.8484	382.2990772
Role_Manager	19359.9439	536.8973849	36.05893	3.9549E-199	18306.68514	20413.20266	18306.68514	20413.20266
City_Metro	4080.577268	432.5938962	9.432813	1.71603E-20	3231.935938	4929.218599	3231.935938	4929.218599
Previous CTC	0.451593157	0.033499723	13.4805	6.47831E-39	0.385875055	0.517311259	0.385875055	0.517311259
Previous job cl	-29.04107129	192.2225195	-0.15108	0.879935155	-406.1337121	348.0515695	-406.1337121	348.0515695
Graduation ma	-3.65235016	14.51823866	-0.25157	0.80141251	-32.1335134	24.82881308	-32.1335134	24.82881308
Exp (Months)	258.940639	15.50315085	16.70245	5.36078E-57	228.5273237	289.3539543	228.5273237	289.3539543

Analysis:

The Significance F Value: 4.4389 x e^{-264}
Significance f value is low between the predictor variable & the response variable, thereby suggesting that the Group means are clustered close together with low variability.

Hence, there is a Significant relationship between x-independent variables & y-dependent variable.

Accuracy:

Adjusted R Square = 0.6

Adjusted R Squared value of the regression between the groups of independent & dependent variables is low. Therefore, suggesting that the input of additional factors, will have a negligible difference in proportions of variations in the respective effect variable/factor-CTC, with respect to the cause variables identified above.

Thus, the Accuracy for our linear regression model is efficient.

In order to measure the effectiveness of magnitude of the different cause variables which influence the effect variable, the p value of the statistical model is analysed.

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	32438.76192	2166.322566	14.97411	5.83E-47	28188.97735	36688.54649	28188.97735	36688.54649
College_T1	4659.731658	537.5128706	8.669061	1.24675E-17	3605.265468	5714.197848	3605.265468	5714.197848
College_T2	-832.2746616	619.1275007	-1.34427	0.179090432	-2046.8484	382.2990772	-2046.8484	382.2990772
Role_Manager	19359.9439	536.8973849	36.05893	3.9549E-199	18306.68514	20413.20266	18306.68514	20413.20266
City_Metro	4080.577268	432.5938962	9.432813	1.71603E-20	3231.935938	4929.218599	3231.935938	4929.218599
Previous CTC	0.451593157	0.033499723	13.4805	6.47831E-39	0.385875055	0.517311259	0.385875055	0.517311259
Previous job cl	-29.04107129	192.2225195	-0.15108	0.879935155	-406.1337121	348.0515695	-406.1337121	348.0515695
Graduation ma	-3.65235016	14.51823866	-0.25157	0.80141251	-32.1335134	24.82881308	-32.1335134	24.82881308
Exp (Months)	258.940639	15.50315085	16.70245	5.36078E-57	228.5273237	289.3539543	228.5273237	289.3539543

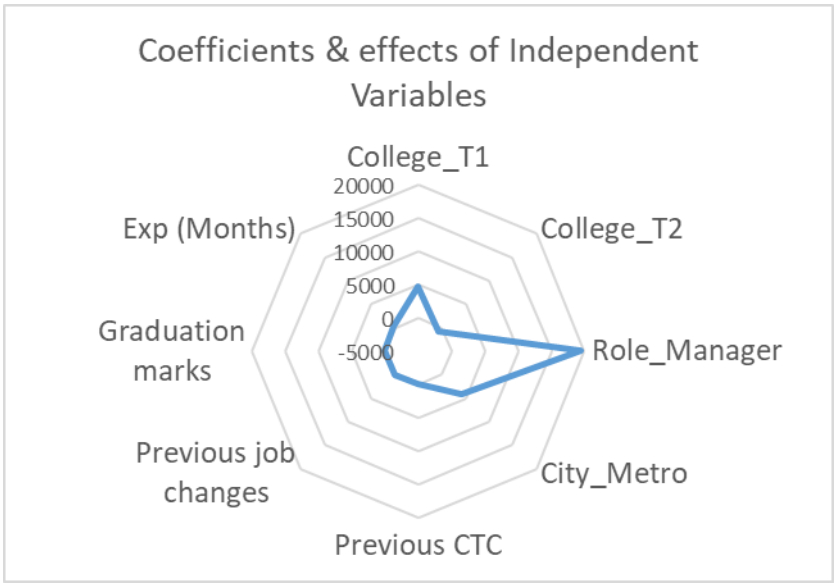


Figure 25. Effects of Variables-Coefficients

X-Variables or Independent Variables that have the highest influence over the statistical y-variable or Effect Variable are:

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	32438.76192	2166.322566	14.97411	5.83E-47	28188.97735	36688.54649	28188.97735	36688.54649
College_T1	4659.731658	537.5128706	8.669061	1.24675E-17	3605.265468	5714.197848	3605.265468	5714.197848
Role_Manager	19359.9439	536.8973849	36.05893	3.9549E-199	18306.68514	20413.20266	18306.68514	20413.20266
City_Metro	4080.577268	432.5938962	9.432813	1.71603E-20	3231.935938	4929.218599	3231.935938	4929.218599
Previous CTC	0.451593157	0.033499723	13.4805	6.47831E-39	0.385875055	0.517311259	0.385875055	0.517311259
Exp (Months)	258.940639	15.50315085	16.70245	5.36078E-57	228.5273237	289.3539543	228.5273237	289.3539543

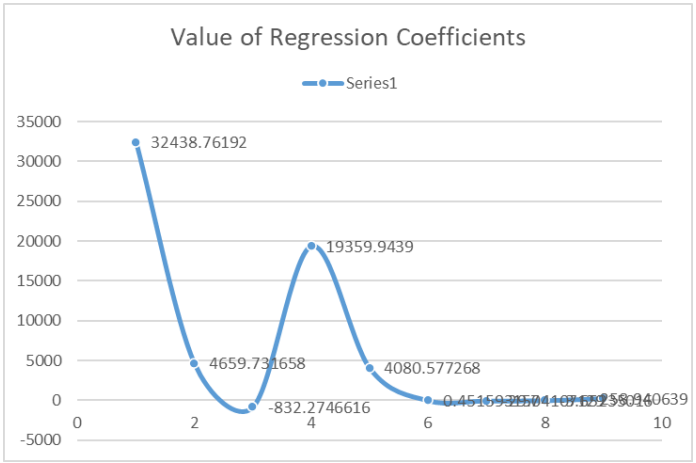
Simple Linear Regression

$$y = b_0 + b_1 * x_1$$

Multiple Linear Regression

Dependent variable (DV) Independent variables (IVs)

$$y = b_0 + b_1 * x_1 + b_2 * x_2 + \ldots + b_n * x_n$$



V. Predictions: Predict CTC Values for New Employees

			Intercept	College_T1	College_T	Role_Manager	City_Metro	Previous CTC	Previous j	Graduatio	Exp (Months)		
			32438.76192	4659.73166	-832.275	19359.9439	4080.577268	0.45159316	-29.0411	-3.65235	258.940639		
S.No.	College	Role	City type	College_T1	College_T	Role_Manager	City_Metro	Previous CTC	Previous j	Graduatio	Exp (Months)	CTC	Predicted CTC
1	Tier 1	Manager	Non-Metro	1	0	1	0	55,523.00	3	66	19	71,406.58	86,123.94
2	Tier 2	Executive	Metro	0	1	0	1	57,081.00	1	84	18	68,005.87	65,789.55
3	Tier 2	Executive	Metro	0	1	0	1	60,347.00	2	52	28	76,764.02	69,941.69
4	Tier 3	Executive	Metro	0	0	0	1	49,010.00	2	81	33	82,092.39	66,843.04
5	Tier 3	Executive	Metro	0	0	0	1	57,879.00	4	74	32	73,878.10	70,556.76
6	Tier 2	Executive	Non-Metro	0	1	0	0	54,340.00	4	73	31	59,950.89	63,790.43
7	Tier 2	Executive	Non-Metro	0	1	0	0	60,298.00	1	42	46	66,602.34	70,565.48
8	Tier 3	Executive	Non-Metro	0	0	0	0	49,944.00	2	56	37	57,768.44	64,311.32
9	Tier 1	Executive	Metro	1	0	0	1	53,124.00	4	40	37	70,083.30	74,488.05
10	Tier 3	Executive	Non-Metro	0	0	0	0	51,141.00	1	47	60	85,648.48	70,869.42

Through the means of regression, after the identification of variables, & data pre-processing, we can run linear regression over the given data to estimate the predicted CTC for the respective individuals with dependent variable as the Current CTC & Independent Variable as College Type, Role/Designation, City/Work Location, Previous CTC, Number of Changes in Jobs, Graduation Marks, & Work Experience in Months.

Multiple Linear Regression Formula

$$yi = \beta 0 + \beta 1xi1 + \beta 2xi2 + \ldots + \beta pxip + \epsilon$$

Where:

- **yi** is the dependent or predicted variable
- **β0** is the y-intercept, i.e., the value of y when both xi and x2 are 0.
- **β1** and **β2** are the regression coefficients that represent the change in y relative to a one-unit change in **xi1** and **xi2**, respectively.
- **βp** is the slope coefficient for each independent variable
- **ϵ** is the model's random error (residual) term.

Therefore, in order to evaluate a CTC for a potential candidate,

1) Identify the Independent variables
2) Identify the dependent variables
3) Apply Multi linear regression in order to classify the Cost to Company to be offered based upon cause variables such as- Role, Work Location, Previous CTC, Experience, College of Graduation, & Number of Job Changes.

4.2. Concluding remarks

This chapter detailed the empirical analysis based on the factors that may impact the scope of dependent variables & independent variables in HR Management based upon the case study data of ABB. The next chapter discusses the recommendations and conclusions of the study.

4.3. Data for the case study

Table 2- Case Study: Data of employees for ABB for the month of July, 2015-2017. The data is segregated for the candidates hired for the role/designation of Managers & Executives.

Sample Size: **1338**

Link for the data table- **Table 2-Case Study:**

- https://drive.google.com/file/d/1F3uI9xYzmpcoSRI6JmKrnYSE98HrS1fK/view?usp=sharing,
- https://www.kaggle.com/pavansubhasht/ibm-hr-analytics-attrition-dataset

			Intercept	College_T1	College_T	Role_Manager	City_Metro	Previous CTC	Previous j	Graduatio	Exp (Months)		
			32438.76192	4659.73166	-832.275	19359.9439	4080.577268	0.45159316	-29.0411	-3.65235	258.940639		
S.No.	College	Role	City type	College_T1	College_T	Role_Manager	City_Metro	Previous CTC	Previous j	Graduatio	Exp (Months)	CTC	Predicted CTC
1	Tier 1	Manager	Non-Metro	1	0	1	0	55,523.00	3	66	19	71,406.58	86,123.94
2	Tier 2	Executive	Metro	0	1	0	1	57,081.00	1	84	18	68,005.87	65,789.55
3	Tier 2	Executive	Metro	0	1	0	1	60,347.00	2	52	28	76,764.02	69,941.69
4	Tier 3	Executive	Metro	0	0	0	1	49,010.00	2	81	33	82,092.39	66,843.04
5	Tier 3	Executive	Metro	0	0	0	1	57,879.00	4	74	32	73,878.10	70,556.76
6	Tier 2	Executive	Non-Metro	0	1	0	0	54,340.00	4	73	31	59,950.89	63,790.43
7	Tier 2	Executive	Non-Metro	0	1	0	0	60,298.00	1	42	46	66,602.34	70,565.48
8	Tier 3	Executive	Non-Metro	0	0	0	0	49,944.00	2	56	37	57,768.44	64,311.32
9	Tier 1	Executive	Metro	1	0	0	1	53,124.00	4	40	37	70,083.30	74,488.05
10	Tier 3	Executive	Non-Metro	0	0	0	0	51,141.00	1	47	60	85,648.48	70,869.42
11	Tier 1	Executive	Metro	1	0	0	1	49,497.00	1	50	25	74,914.15	69,793.43
12	Tier 2	Manager	Non-Metro	0	1	1	0	50,197.00	2	66	62	85,219.39	89,390.24
13	Tier 1	Executive	Metro	1	0	0	1	63,234.00	4	73	23	82,910.94	75,307.96
14	Tier 2	Executive	Non-Metro	0	1	0	0	60,059.00	2	71	56	74,350.08	72,912.00
15	Tier 2	Manager	Metro	0	1	1	1	66,487.00	1	50	27	1,03,595.83	91,851.82
16	Tier 1	Executive	Metro	1	0	0	1	49,292.00	4	49	19	70,729.63	68,063.74
17	Tier 1	Executive	Non-Metro	1	0	0	0	55,400.00	4	48	52	70,051.94	75,290.19
18	Tier 1	Executive	Metro	1	0	0	1	53,089.00	2	72	23	69,403.49	70,788.28
19	Tier 1	Executive	Metro	1	0	0	1	69,345.00	3	79	56	84,710.53	86,619.82
20	Tier 1	Manager	Metro	1	0	1	1	63,508.00	1	48	30	95,879.94	96,782.66
21	Tier 1	Executive	Non-Metro	1	0	0	0	60,057.00	1	61	60	73,487.13	79,504.43
22	Tier 1	Executive	Non-Metro	1	0	0	0	52,402.00	3	35	30	61,597.98	68,316.14
23	Tier 2	Executive	Metro	0	1	0	1	60,180.00	2	68	18	63,119.80	67,218.43
24	Tier 1	Manager	Non-Metro	1	0	1	0	53,422.00	4	44	34	98,586.83	89,110.56
25	Tier 3	Executive	Metro	0	0	0	1	49,857.00	3	37	37	71,502.56	68,392.96
26	Tier 2	Executive	Non-Metro	0	1	0	0	48,682.00	3	82	59	64,320.67	68,481.83
27	Tier 1	Executive	Non-Metro	1	0	0	0	48,516.00	2	37	63	77,310.22	75,128.03

Chapter 5

5. Recommendations & Conclusions

This chapter details the recommendations and conclusion of the study 'Scope of Marketing in Rural India' based on the analysis and findings.

5.1. Recommendations

Human Resource analytics will encounter multiple obstacles in order to develop into a domain with minimal fault tolerance. Initially, It is based upon studies that are still under-development, thereby, the results imposed by the respective analytics consists of multiple drawbacks. Therefore, Organizations have to accept the generic fundamentals of analytics & machine learning. However, the development in the respective sector entails an Everest of a magnitude, as industries, scholars & academic researchers are constantly discovering new fundamental developments in order to increase the accuracy of the models & overshadowing their proprietary underpinnings.

Urbanization of Big Data in industries belonging to different tiers, irrespective of the sector, allows them to make strategic decisions with quantitative foundations. However, the Workforce Analytics & Human Resource Capital Management is the only branch that has to deal with employee's feelings & emotions, labour laws, & compliances in a spontaneous ecosystem, thereby, generating contradictions within their arbitrary system. Therefore, development of a grey area, where intuition-based rationale coincides with Quantitative reasoning holds a severe importance within the organisation, where the judgement of executives is justified, strategic, & fair.

Fault Tolerance is rarely defined in our analytical structures, because this term is rarely used during the period of technological revolution. However, due to increase in data & pivotal proliferation of 'Big Data' has caused us to ponder over the factual importance of fault tolerance within our predefined models. As the data increases, the rate of error increases, & fault tolerance is a cumulative concept where the error defined by the analysis is exponentially increased through the interference of factors present within the system. Optimization of Analytics, that is, the effect of one or more variable over the other factors which is enumerated to our problem equation/system, thus, altering & changing the values at a rate that demolishes our analytical prejudice & conclusions. Therefore, Studies related to the rate of error & their effects over the strategies identified & derived through analytics within the complex structures of an organisation is necessary.

Investment in Analytics is extremely important for a corporation to achieve a competitive edge within the Institutional Jungle. Investment will allow the analytical departments to overcome generic issues like:

- Data Quality
- Data Inconsistencies
- Accessibility
- Analytical Acumen, and Research & Development
- Cultural Norms, etc.

5.2. Conclusions

Analytics is still in its nascent development phase; thus, it requires extreme surgical oversight over how the respective tool should be used and adapted within the functioning systems of the organisation. There is a generic difference in how the data is used within the corporate economy; thus, defining a fundamental trend that analytical rationale is embedding itself within the cockles of the organizational strategies.

Progress in data analytics is being aggressively pursued by scholars, academic researchers, institutions & organisation to develop a 'perfect system' to deal with strategies & provide inferences derived from internal & external factors. Human resource capital management through the means of analytics pose a severe potential.

Human resource domain requires a necessary skill, will to accept analytics, identification of organizational requirements to generate organizational strategies, & an efficient approach to analytical system. Development of Human Resource & Data Science will lead to a development of a new sectorial domain within the organisation, thus, marking the initial stage of technological-data-driven revolution

5.3. Concluding Remark

This chapter discussed the recommendations and the conclusions based upon the nature of analytics & human resource analytics. The following chapter discusses the limitations and the scope of further research that may be conducted.

Chapter 6

6. Limitations

To allow researchers with insight for further analysis, this chapter presents the limitation of study and scope for further work. The limitations of the study can be overcome when available with required resources such as manpower, time, and technology.

6.1. Limitations of the Research

The study uses secondary data that was defined & processed, thereby, it may not be accurate or reliable. The case analysis uses an incomplete form of data for Human Resource Employee data personal information which was available & accessible for analysis. Recent data may help in shedding light on the recent trend analysis for human resource development. Moreover, there is a chance that the pandemic Covid-19 could impact the trends, organizations and marketer's mindset and focus. There is a possibility of drastic changes in the investment for Analytics in Human Resource domain due to the economy. Despite these limitations, this study has provided several important insights.

Chapter 7

7. References

1. Bass, Dina and Rodrigo Orihuela, “Help Wanted: Black Belts in Data”, Bloomberg Businessweek, June 4th 2015.
2. Becker, Brian and Mark Huselid, “Measuring HR? Benchmarking is Not the Answer!”, HR Magazine, December 2003.
3. Bersin, Josh, Karen O’Leonard and Wendy Wang-Audia, High-Impact Talent Analytics: Building a World-Class HR Measurement and Analytics Function, Bersin by Deloitte, October 7th 2013.
4. Bersin, Josh, “Big Data in Human Resources: A World of Haves and Have-Nots”, Forbes, October 7th 2013.
5. Bersin, Josh, The Datafication of HR. Deloitte University Press, Deloitte Review, Issue 14, January 17th 2014.
6. Bolton, Robert and Mark Spears, Evidence-based HR. KPMG Advisory Institute with the Economist Intelligence Unit, May 4th 2015.
7. Boudreau, John W., “Reimagining HR: The Paradox of a Profession at the Tipping Point”, People + Strategy, 38.4 (2015): pp. 46-55 Boudreau, John W. and Peter M. Ramstad, Beyond HR. Boston, MA: Harvard Business Publishing, 2007 CareerBuilder, “Number of Employers Passing on Applicants Due to Social Media.
8. Carlson, Kevin D. and Michael J. Kavanagh, HR Metrics and Workforce Analytics. Sage Publishing, 2014.
9. Cascio, Wayne and John Boudreau, Investing in People. Upper Saddle River, New Jersey: Pearson Education, 2011 Charan, Ram, “It’s time to split HR”, Harvard Business Review, July 2014.
10. Coco, Cedric T., Fiona Jamison and Heather Black, “Connecting People Investments and Business Outcomes at Lowe’s”, People & Strategy 34.2 (2011): pp. 28-33.
11. https://hbr.org/2010/10/competing-on-talent-analytics Dekas, Kathryn, “People Analytics: Using Data to Drive HR Strategy and Action”, Presentation, Strata Jumpstart, New York, NY, September 19th 2011.
12. Schatsky, David and Jeff Schwartz, *Global Human Capital Trends 2015*, Deloitte University Press (http://d2mtr37y39tpbu.cloudfront.net/wp-content/uploads/2015/08/DUP_GlobalHumanCapitalTrends2015.pdf)
13. Talent Management Diversity Executive Staff, “CEOs Who Lead the Way”, *Talent Management*, September 11th 2008 (http://www.talentmgt.com/articles/ceos-who-lead-the-way)
14. Tata Consultancy Services, *The Emerging Big Returns of Big Data*, 2013 (http://www.tcs.com/SiteCollectionDocuments/Trends_Study/TCS-Big-Data-Global-Trend-Study-2013.pdf)
15. Tyler, Richard, “Workers over 60 are surprise key to McDonald’s sales”, *The Telegraph*, August 13th 2009 (http://www.telegraph.co.uk/finance/newsbysector/retailandconsumer/6017391/Workers-over-60-are-surprise-key-to-McDonalds-sales.html)
16. Visier, *2014 Survey Report—The State of Workforce Analytics and Planning*

17. Voelker, Rebecca, “Hot jobs: Big-data psychologists”, *grad PSYCH Magazine*, January 2013.
18. Harvard Business Review Analytic Services (HBR-AS), sponsored by Visier, HR Joins the Analytics Revolution, August 2014.
19. Harvard Business Review Analytic Services and Visier, via Bersin, Demand for HR Analytics Roles Strong, but Slowing, May 17th 2015.
20. Hastie, Trevor, Robert Tibshirani and Jerome Friedman, The Elements of Statistical Learning. New York, NY: Springer New York Inc., 2001.
21. Huselid, Mark A., “The impact of human resource management practices on turnover, productivity and corporate financial performance”, Academy of Management Journal, 1995, Vol. 38, No. 3, pp. 635-872.
22. Huselid, Mark A., Brian E. Becker and Dave Ulrich, The HR Scorecard: Linking People, Strategy, and Performance. Boston, MA: Harvard Business Review Press, 2001.
23. Huselid, Mark A., Brian E. Becker and Richard W. Beatty, The Workforce Scorecard: Managing Human Capital to Execute Strategy. Boston, MA: Harvard Business School Publishing, 2005 Huselid, Mark A., Brian Becker and Richard Beatty, The Differentiated Workforce: Transforming Talent into Strategic Impact. Boston, MA: Harvard Business School Publishing, 2009.

turnitin

Project Dissertation Report_073-Plagiarism Check.docx
May 21, 2021
5944 words / 34216 characters

Project Dissertation Report_073-Plagiarism Check.docx

Sources Overview

11%

OVERALL SIMILARITY

1	Southern New Hampshire University - Continuing Education on 2021-02-22 SUBMITTED WORKS	8%
2	www.coursehero.com INTERNET	1%
3	www.datasciencecentral.com INTERNET	<1%
4	cbo.gov.om INTERNET	<1%
5	Hamdan Bin Mohammed Smart University on 2020-04-24 SUBMITTED WORKS	<1%
6	www.yumpu.com INTERNET	<1%
7	Boston University on 2012-07-30 SUBMITTED WORKS	<1%
8	Intercollege on 2017-01-08 SUBMITTED WORKS	<1%
9	fr.scribd.com INTERNET	<1%
10	goodanswers.wishessays.info INTERNET	<1%
11	tsukuba.repo.nii.ac.jp INTERNET	<1%
12	es.scribd.com INTERNET	<1%
13	jfmueller.faculty.noctrl.edu INTERNET	<1%

Excluded search repositories:

- None

Excluded from Similarity Report:

- Bibliography
- Quotes
- Small Matches (less than 8 words).

Excluded sources: