

**ASSESSMENT OF EMPLOYEE ATTRITION AND MAXIMIZING EMPLOYEE
RETENTION: LEVERAGING BUSINESS INTELLIGENCE TOOLS FOR
DATA-DRIVEN HR DECISION MAKING**

by

KAMESWARI. JADA, MBA-HR; HR-ANALYTICS

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DATA-DRIVEN HR DECISION MAKING**

by

KAMESWARI. JADA

APPROVED BY

Dr. Aaron Nyanama



Chair

Dr. Luka Lesko

Co Chair



Dr. Hemant Palivela

Thesis Supervisor



RECEIVED/APPROVED BY:

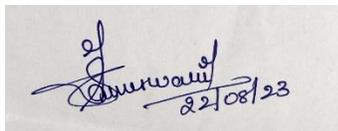
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DECLARATION

I, the undersigned, **KAMESWARI. JADA**, declare that this thesis, titled “**ASSESSMENT OF EMPLOYEE ATTRITION AND MAXIMIZING EMPLOYEE RETENTION: LEVERAGING BUSINESS INTELLIGENCE TOOLS FOR DATA-DRIVEN HR DECISION MAKING,**” is my original work, which I have done after registering for the degree of **DOCTOR OF BUSINESS ADMINISTRATION** at **SWISS SCHOOL OF BUSINESS AND MANAGEMENT GENEVA**. I have not submitted this thesis or any part of it to any other institution for any degree, diploma, or qualification. I have acknowledged all the sources of information and data that I have used in this thesis. I have also obtained the necessary permissions for any copyrighted material I have included in this thesis.

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Name:

KAMESWARI. JADA

DEDICATION

This thesis is dedicated to the HR sector, HR analysts, and a team of people analytics who are struggling a lot to cope with the challenges and opportunities of the changing world of work. They are the ones who are responsible for managing, developing, and retaining the most valuable asset of any organization: its human capital. They are the ones who are applying data-driven insights and evidence-based practices to improve organizational performance, employee engagement, and well-being. They are the ones who are creating a positive impact on society and the economy through their work. They deserve recognition, appreciation, and support for their efforts and achievements. This thesis is a humble attempt to contribute to their field of knowledge and practice by advocating data-driven decision-making and practice in all the various industries.

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and stood up for me whatever the situation was. I am currently in this position because of them only. They have been my role models, guardians, and benefactors. They have always showered me with their love and blessings.

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TABLE OF CONTENTS

DEDICATION	11
ACKNOWLEDGEMENT	12
TABLE OF CONTENTS.....	XIV
LIST OF TABLES	XXII
LIST OF FIGURES	XXIII
ABSTRACT.....	XXVII
Keywords:	xxviii
CHAPTER I INTRODUCTION.....	29
1.1 INTRODUCTION	29
1.1.1 Digital Technology	29
1.1.2 IT and Analytics Use	29
1.1.3 Big Data	30
1.1.4 Data-Driven Decision-Making (DDDM).....	31
1.1.5 IT Industry in India	32
1.1.6 HR Analytics.....	37
1.1.7 Employee Attrition.....	41
1.2 RESEARCH PROBLEM.....	42
1.2.1 Employee Attrition:	42
1.2.2 Attrition Types:	44
1.3 PURPOSE OF RESEARCH	47
1.3.1 Different Purposes	47
1.3.2. Significant/ Common Triggering Attribute for An Employee to Leave the Organization.....	51
1.3.3 Significance of Predictive Analysis	57
1.3.4. Few Advantages Of The Predictive Attrition	60

1.3.5 Research Purpose	61
1.3.6 Reason for addressing Employee Attrition Problem as a fundamental research problem:	63
1.4 SIGNIFICANCE OF THE STUDY:	65
1.5 RESEARCH GOALS, QUESTIONS, & OUTCOMES	66
1.5.1 Research Goal	66
1.5.2 Research Questions:	67
1.5.3 Benefits Or Impacts Of Our Goals:	68
CHAPTER II REVIEW OF LITERATURE	73
2.1 THEORETICAL FRAMEWORK	73
2.1.1 PEOPLE-ANALYTICS - Attrition Hassle In The Indian IT Industry	73
2.1.2 What Exactly Is Employee Attrition	75
2.1.3 How to Determine the Attrition Rate	76
2.1.4 What exactly is Employee Retention	76
2.1.5 How to Determine the Retention Rate	77
2.1.6 Employee Turnover vs. Employee Attrition	77
2.1.7 Attrition Impacts	79
2.1.8 How attrition impacts an Organization in the long run	79
2.1.9 Few Theories That Explain Employee Attrition Are	80
2.1.10 Recent Trends in people analytics with DDDM	83
2.2 THEORY OF REASONED ACTION	84
2.2.1 Employee Retention Does Influence An Information Technology Company's Overall Success	84
2.2.2 Six Significant Variables In Employee Retention	85
2.3 HUMAN SOCIETY THEORIES / VARIOUS THEORIES APPLIED IN VARIOUS ORGANIZATIONS	87
2.3.1 Google	87
2.3.2 Hewlett-Packard (HP)	88
2.3.3 Juniper's Network	89
2.3.4 Wal-Mart	90

2.4 CONSIDERED DATA POINTS AND THE USE OF DDDM AND PEOPLE ANALYTICS IN THE HR SECTOR TO ADDRESS EMPLOYEE ATTRITION FOR ANALYSIS AND RESULTS BY VARIOUS TOP COMPANIES	91
2.4.1 Google's DNA/ Project Oxygen Model	92
2.4.2 Hewlett-Packard's Significant Turnover Model	92
2.4.3 Xerox Corporation Statistics Evaluation- Recruiting Technique	93
2.4.4 Genpact's FLM Surveys & Overall Performance Rankings	94
2.4.5 Nestlé's "Minitab"	94
2.4.6 Sysco's "Personnel Evaluation"	95
2.4.7 Mindtree "Turnover Modeling"	96
2.4.8 Marico Kaya Ltd- Integrated HR and Predictive Analytics.....	96
2.4.9 Nielsen's "Predictive Risk Model"	97
2.4.10 Walmart's "Analytics Engine."	97
2.4.11 Infosys's Advanced Analytics	98
2.4.12 Capgemini's "Common HR Dashboard"	98
2.4.13 Cisco's HR Advanced Analytics Group	99
2.4.14 Starbucks Reinforcement Learning Technology	100
2.4.15 Adobe's Personalized HRM	100
2.4.16 Samsung's OJT Strategy	101
2.4.17 Godrej centralizes HR processes to serve its employees better	101
2.3.18 McKinsey "Machine Learning Strategy"	102
2.5 HOW WORKER ATTRITION IS, IN THE LONG RUN, IMPACTING THE EMPLOYER	103
2.5.1 Influences the personnel's job security and employee contentment ..	103
2.5.2 Employee Turnover Impact	104
2.5.3 Personnel Wornout and its Impact.....	106
2.5.4 Reduces Work Satisfaction	107
2.6 SUMMARY.....	109
2.7 CONCLUSIONS.....	109
CHAPTER III METHODOLOGY	111
3.1 OVERVIEW OF THE RESEARCH PROBLEM.....	111

3.2 OPERATIONALIZATION OF THEORETICAL CONSTRUCTS.....	114
3.3 RESEARCH PURPOSE AND QUESTIONS	116
3.3.1 Research Purpose	116
3.3.2 The Research Questions.....	118
3.4 RESEARCH DESIGN	119
3.4.1 Quantitative phase.....	119
3.4.2 Qualitative phase.....	120
3.4.3 Decision Tree Analysis	120
3.5 POPULATION AND SAMPLE	120
3.5.1 Population	120
3.5.2 Sample.....	121
3.6 PARTICIPANT SELECTION.....	123
3.7 INSTRUMENTATION	126
3.7.1 KNIME Analytics Platform:	127
3.7.2 Jupyter Notebook	133
3.7.3 Microsoft Excel:.....	134
3.7.4 POWER BI.....	136
3.7.5 Tableau.....	138
3.8 DATA COLLECTION PROCEDURES	140
3.9 DATA ANALYSIS.....	143
3.9.1 Feature Importance Extraction through Random Classifier Method.....	144
3.9.2 Exploratory Data Analysis Based on Qualitative Data.....	147
3.9.3 Model Comparison Analysis Through KNIME.....	154
3.9.4 Decision Tree Analysis and Decision Rule Setting Method In KNIME:.....	166
3.9.5 Tie-up the Machine Learning Model with basic analytics for the organizational automation process:.....	178

3.10 RESEARCH DESIGN LIMITATIONS	186
3.11 CONCLUSIONS.....	187
CHAPTER IV RESULTS.....	188
4.1 QUALITATIVE DATA ANALYSIS(THROUGH POWER BI, JUPYTER- NOTEBOOK, TABLEAU, MS-EXCEL).....	188
4.1.1 Which of the Most Significant Challenges Faced by the Organization	188
4.1.2 Finding Out the Various Reasons for Employee Churn	189
4.1.3 Identify the Impulsive Factors Which Determine Employee Attrition.	190
4.1.4 Which Age Group Is More Susceptible to Employee Attrition	192
4.1.5 Department-Wise Employee Churn:	193
4.1.6 Which Level of Employees Are Susceptible More to Attrition.....	194
4.1.7 Experience Range-Based Attrition	196
4.1.8 Analyze the Employee's Satisfaction with Their Pay for the Job Role.	197
4.1.9 Elevate Significant After-Effects Due to Employee Attrition.	199
4.1.10 Assess Employees Who Feel Overworked and Micromanaged.	200
4.1.11 Evaluate the employee receiving proper training, new opportunities, and growth prospects within the organization.	202
4.1.12 Identify Whether the Company Work Culture Aligns with the Employee's Values and Does the Boss Give Room to Grow.....	203
4.1.13 Employees on Their Expectations in The Post-Pandemic Era from Their Employer	205
4.1.14 Primary Reason For The Increasing No Of Industries Adversely Affecting Employee Retention, Which Leads To Employee Attrition.	206
4.1.15 Evaluate The Organization's Offers To The Resigned Employees If He/She Consents To Continue Their Services.....	208
4.2 QUANTITATIVE DATA ANALYSIS	211
4.2.1 Monthly Income-Age-Job Satisfaction-Employee Attrition Yes or No:	215
4.2.2 Relationship between total working years, distance from home, and attrition of employees:	216
4.2.3 Job Satisfaction Of Employees In India Based On Their Years At The Company And Age	218
4.2.4 Percent Salary Hike Of Employees In India Based On Their Attrition And Average Monthly Hours:	219

4.2.5 Performance Rating Of Employees In India Based On Their Number Of Companies Worked And Job Satisfaction:	220
4.2.6 Distribution Of Decision Skills Possessed By Employees In India Based On Their Attrition	222
4.3 SUMMARY OF FINDINGS	226
4.4 CONCLUSION.....	230
CHAPTER V DISCUSSION	231
5.1 Discussion of Results Based on Qualitative Data.....	231
5.1.1 Discussion on which of The most significant challenges faced by the organization.....	236
5.1.2 Discussion on different causes of employee attrition	238
5.1.3 Discussion on what are the impulsive factors which determine employee attrition	240
5.1.4 Discussion on employee attrition rates and factors of different age groups in the organization.....	243
5.1.5 Discussion on Department-Based Employee Attrition:.....	244
5.1.6 Discussion on Employee Attrition at the Management level.....	245
5.1.7 Discussion on Employee Attrition by Experience Range.....	247
5.1.8 Discussion on Employee Satisfaction with their Pay for the job role.....	249
5.1.9 Discussion on Significant after-effects due to employee attrition	251
5.1.10 Discussion on Employees who feel overworked and Micromanaged.....	255
5.1.11 Discussion On Employees Receiving Proper Training, New Opportunities, And Growth Prospects Within The Organization.....	256
5.1.12 Discussion on company culture, employee values, and boss support.....	258
5.1.13 Discussion on Employees on their expectations in the post-pandemic era from their employer:	260
5.1.14 Discussion on the primary reason for the increasing number of industries adversely affecting employee retention:.....	262
5.1.15 Discussion on the organization's offers to the resigned employees if he/she consents to continue their services	265

5.2	DISCUSSION ON QUANTITATIVE DATA ANALYSIS	268
5.2.1	Discussion on employee attrition based on monthly income, age, and job satisfaction	268
5.2.2	Discuss employee attrition based on total working years, distance from home, and job satisfaction.	269
5.2.3	Discussion On Employee Attrition Based On Years At Company, Age, And Job Satisfaction	271
5.2.4	Discussion on employee attrition based on attrition, average monthly hours, and percent salary hike.....	273
5.2.5	Discuss employee attrition based on the number of companies worked, performance rating, and job satisfaction.	275
5.2.6	Discussion on employee attrition based on decision skills possess..	277
5.2.7	Discussion on employee attrition based on department	279
5.2.8	Discussion on the Correlation Plot And Relationship Between the Features	280
5.3	DISCUSSION ON VARIOUS DECISION RULES:	282
5.3.1	Rule on monthly income, worked at the company job level, and over time	284
5.3.2	Rule on worked at company, distance from home, stock options level, job level, and overtime.....	284
5.3.3	Rule on decision skill, worked at company, distance from home, stock options level, job level, and over time	285
5.3.4	Rule on no of projects worked at the company, stock options level, job level, and over time.....	286
5.3.5	Rule on no of projects, monthly income, distance from home, total working years, stcoplvl, job level, over time	286
5.3.6	Rule on environment satisfaction, avg_monthly_hrs, business travel, total working years, overtime	287
5.3.7	Rule on years at company, department, work-life balance, environment satisfaction, avg_monthly_hrs, business travel, total working year, overtime	289
5.3.8	Rule on avg_monthly_hrs, job satisfaction, age, department, years at the company, stcoplvl, total working years, over time	290
5.3.9	Rule on percent salary hike, gender, education, stcoplvl, worked at comp, job level, and overtime.....	291
5.3.10	Rule on YearsWithCurrManager, YearsSinceLastPromotion, WorkedAtComp, DistanceFromHome, StcOpLvl, JobLevel, Overtime	292

5.3.11 Rule on monthly income, worked at the company, job level, over time	293
5.3.12 Rule on Decision_skill_possess, WorkedAtComp, DistanceFromHome, StcOpLvl, JobLevel, and OverTime.....	293
5.3.13 Rule On Worked At Company, Distance From Home, Stock Options Level, Job Level, And Overtime.....	294
5.3.14 Rule on average monthly hours, total working years, worked at company, distance from home, stock options level, job level, and over time	295
5.3.15 Rule On N_Projects, Monthly Income, Distancefromhome, Totalworkingyears, Stcoplvl, Joblevel, And Overtime.....	296
5.3.16 Rule on the department, work-life balance, environment satisfaction, avg monthly hours, business travel, total working years, and overtime	296
5.3.17 Rule On Percentsalaryhike, Joblevel, Age, Workedatcomp, Work life balance, Stcoplvl, Totalworkingyears, And Overtime.....	297
5.3.18 Rule on work-life balance, worked at company, age, department, years at the company, StcOpLvl, TotalWorkingYears, and OverTime	298
5.3.19 Rule on gender, years at company, stcoplvl, total working years, and over time	299
5.3.20 Rule on years with current manager, worked at the company, stcoplvl, total working years, and over time	300
5.3 RETENTION STRATEGIES	301
5.3.1 Employee Salary-Related Retention Strategies:	301
5.3.2 Employee Non-Monetary Retention Strategies:	303
5.3.3 Employee Work-Related Retention Strategies:	304
5.3.4 Employee Personal-Related Retention Strategies.....	306
5.3.5 Few Other Retention Strategies.....	307
CHAPTER VI SUMMARY, IMPLICATIONS, AND RECOMMENDATIONS	309
6.1 SUMMARY	309
6.2 IMPLICATIONS	315
6.3 RECOMMENDATIONS FOR FUTURE RESEARCH.....	317
6.4 CONCLUSION.....	319

REFERENCES325

LIST OF TABLES

Table 0:1 Feature Description of the Considered Data 57



LIST OF FIGURES

<i>Figure 1 Why Data-Driven Decision Making Is Important</i>	31
<i>Figure 2 Key segments of the Global IT Market</i>	33
<i>Figure 3 IT Industry key milestones</i>	35
<i>Figure 4 IT Sector Rising Attrition Levels</i>	37
<i>Figure 5 Data-Driven Decision Making In HR</i>	38
<i>Figure 6 Illustrating the usage of various types of people analytics during Time</i>	40
<i>Figure 7 Employee Attrition Types</i>	45
<i>Figure 8 Attrition Percentage Over the past Five Quarters</i>	50
<i>Figure 9 Drivers of Employee Turnover</i>	51
<i>Figure 10 Predictive Analytics Use Cases</i>	58
<i>Figure 11 Few advantages of Predictive Attrition</i>	60
<i>Figure 12 Mc Kinsey's Great Attrition or Great Resignation</i>	62
<i>Figure 13 Types of Analytics</i>	73
<i>Figure 14 Employee Turnover vs. Employee Attrition</i>	77
<i>Figure 15 Represents the various names in usage for the HR Analytics term.</i>	83
<i>Figure 16 KNIME Analytics Platform Appearance</i>	127
<i>Figure 17 Example of KNIME work flow and CSV file Reading</i>	128
<i>Figure 18 Jupyter Notebook appearance and CSV File Reading</i>	133
<i>Figure 19 Microsoft Excel Appearance during Data Analysis</i>	134

<i>Figure 20 Microsoft Power BI tool in Data Analysis</i>	137
<i>Figure 21 Random Forest Attribute Classifier</i>	146
<i>Figure 22 CRISP-DM methodology to explain various phases in analytics</i>	149
<i>Figure 23 CSV File reading to Normalizer node connectivity in KNIME</i>	151
<i>Figure 24 Exploring the data for Prediction -Normalizer to Partitioning</i>	152
<i>Figure 25 Predictive model comparison Using KNIME Analytics(EDA)</i>	153
<i>Figure 26 Random Forest Prediction Model and its Nodes Connectivity</i>	154
<i>Figure 27 RF- ROC Curve and its Value</i>	155
<i>Figure 28 Support Vector Machine Prediction Model and its Nodes Connectivity</i>	156
<i>Figure 29 SVM ROC Curve and its Value</i>	156
<i>Figure 30 Logistic Regression Analysis Prediction Model and its Nodes Connectivity</i>	158
<i>Figure 31 LR-ROC Curve and its Value</i>	158
<i>Figure 32 K-Nearest Neighbour Prediction model and Nodes connectivity</i>	159
<i>Figure 33 KNN-ROC Curve and its value</i>	160
<i>Figure 34 Tree Ensemble Model Prediction and Node Connectivity</i>	161
<i>Figure 35 Tree Ensemble Curve and its Value</i>	162
<i>Figure 36 Model Comparision Bar Graph</i>	163
<i>Figure 37 Decision Tree Analysis and Nodes Connectivity</i>	166
<i>Figure 38 Decision Tree Rule based on Condition</i>	169
<i>Figure 39 Decision Tree Image</i>	170

<i>Figure 40 PMML Rule set- Decision Tree Ruleset.</i>	171
<i>Figure 41 Decision Tree Rule Set Table</i>	172
<i>Figure 42 Data to Machine Learning Operations(MLOps) end-to-end Process Flow chart</i>	178
<i>Figure 43 Greatest HRM Challenges</i>	188
<i>Figure 44 Various Reasons for Employee Churn</i>	189
<i>Figure 45 Impulsive Factors Which Determine Employee Attrition</i>	190
<i>Figure 46 age-based on employee attrition.</i>	192
<i>Figure 47 Department-Wise Employee Churn</i>	193
<i>Figure 48 Management Level-based employee attrition</i>	194
<i>Figure 49 Experience Range-Based Attrition</i>	196
<i>Figure 50 Compensation-related Employee satisfaction level</i>	197
<i>Figure 51 Significant After-Effects Due to Employee Attrition</i>	199
<i>Figure 52 Employees' Opinions on Overworked and Micromanaged</i>	201
<i>Figure 53 proper training, new opportunities, and growth prospects within the organization.</i>	202
<i>Figure 54 Company work culture and boss allow room to grow</i>	204
<i>Figure 55 Employee expectations during the post-pandemic era</i>	205
<i>Figure 56 Reasons for increasing employee attrition in industries</i>	207
<i>Figure 57 Various retention strategies</i>	209
<i>Figure 58 Relationship between Monthly Income-Age--Attrion-Job satisfaction</i>	215
<i>Figure 59 Attrition view based on monthly income-age-job satisfaction.</i>	215

<i>Figure 60 Attrition View based on total working years vs. distance from home</i>	216
<i>Figure 61 Total working years-Distance from home- Job satisfaction- Attrition</i>	217
<i>Figure 62 Job satisfaction vs. Years at the company-age</i>	218
<i>Figure 63 Percent of salary hike vs. Average monthly hours</i>	219
<i>Figure 64 no of companies worked vs. Performance Rating reference to attrition.</i>	220
<i>Figure 65 Attrition view based on no of companies worked vs. performance rating.</i>	221
<i>Figure 66 Attrition based on Decision Skill</i>	222
<i>Figure 67 Attrition view based on decision skill</i>	222
<i>Figure 68 Department vs. Attrition</i>	223
<i>Figure 69 Attrition View based on Department</i>	224
<i>Figure 70 Correlation plot</i>	225

ABSTRACT

**ASSESSMENT OF EMPLOYEE ATTRITION AND MAXIMIZING EMPLOYEE
RETENTION: LEVERAGING BUSINESS INTELLIGENCE TOOLS FOR
DATA-DRIVEN HR DECISION MAKING**

**KAMESWARI. JADA
2023**

Dissertation Chair: <Chair's Name>
Co-Chair: <If applicable. Co-Chair's name>

Data-Driven Decision Making(DDDM) through Artificial Intelligence Tools in Human Resource Management is the tactical method for a business enterprise's optimistic and systemic administration. This expedition pursues to identify the most common and paramount triggering attributes, the knowledge gap between Data-Driven Decision Making through AI Tools, HRM (Human Resources Management), and an organization's Employee Attrition Rate.

How artificial intelligence might be anticipated to avert employee turnover. By applying classification, impact, and employee behavioral analysis, Decision Tree Analysis to qualitative and quantitative & Decision rules framing to the company, HR leaders can gain accurate insights into the perception of the company's employer brand. The employee Attrition Case Study Dataset used is an anecdotal dataset that tries to figure out the most triggering variables that determine employee behavioral aspects toward attrition. Six approaches are employed to categorize attributes.

Employees' monthly earnings, age, average monthly hours worked, distance from home, cumulative working years, years with the firm percentage of pay increase, The number of firms that worked, Stock options level, job function, and an array of other criteria must be considered. A feature importance extraction approach is designed to study each latent factor. The findings also show feasible hypotheses that help enhance employee engagement, reinvent the worker dynamic, and higher levels of risk decrease attrition rates.

All significant variables in employee attrition in the Indian IT business are in employee attrition.

This research adds various Business Intelligence tools like Microsoft Power BI, Tableau, WEKA, and KNIME for Data-Driven Decision Making; based on the findings, our expedition goes with Retention Strategies Impact Analysis on particular groups of employees to the theory development of behavioral elements in People Analytics based on Artificial Intelligence.

Keywords:

Data-Driven Decision making; Employee Attrition; HRM, Artificial Intelligence; People Analytics; Business Intelligence Tools; Employee Behavioral aspects.

CHAPTER I

INTRODUCTION

1.1 INTRODUCTION

1.1.1 Digital Technology

The application of digital technology to produce corporate value has generated enormous quantities of data, which must be used in decision-making. Although significant empirical evidence in established nations supports a favorable relationship between informed decision-making and company success, there is little to no evidence of large-scale research in an emerging economic situation. Furthermore, no empirical information exists on how Data-Driven Decision-Making(DDDM) influences Talent Acquisition, Employee Attrition, Retention, and Productivity within emerging nations' IT sectors.

1.1.2 IT and Analytics Use

The use of IT and analytics has increased significantly over the past decade (Fayolle, 2016)¹, which encourages decision-makers to rely more on these analytics and related technologies rather than relying on their expertise and intuition while making

¹ (Fayolle, 2016)

decisions ((Ammara and Al-Faryan, 2023)¹. In brief, when companies adopt a data perspective to create value, they become more interested in "what do we know" instead of "what do we think." They are no more going "with the gut" and understand that digitalization-induced data provide an unprecedented opportunity to extract information for informed decision-making (Corea, 2016)².

1.1.3 Big Data

In the age of big data, the accessibility to data, followed by insights derived from data for informed decision-making, is changing the global business environment (Gupta S. a., 2021)³. As a result, industries are reshaping their business models and practices with insights obtained from data to become more agile and responsive to external and internal environments, thus creating competitive advantages for survival, growth, and sustainability. With the help of data analytics, business managers can anticipate future trends, forecast risks, and understand the dynamics of their business. Data must be efficiently disseminated to managers in decision-making. Otherwise, the resources input in working on data are wasted (Schrage, 2016)⁴.

¹ (Ammara and Al-Faryan, 2023)

² (Corea, 2016)

³ (Gupta S. a., 2021)³.

⁴ (Schrage, 2016)

1.1.4 Data-Driven Decision-Making (DDDM)

Why is Data-Driven Decision Making so essential nowadays? Why is the organization giving more prioritization to this phenomenon illustrated in the picture? The driving force behind the development of Data-Driven Decision Making (DDDM) is the growing investment trend in IT and analytics. Worldwide IT spending in 2022 is about to exceed US\$4.4 trillion, a 4% increase over 2021, and future IT spending is expected to increase continuously (Gul, 2023)¹. Another report indicates that companies are growing their revenue spending on digital technologies from 3.5% in 2020 to 4.7% in 2021, estimated at 0.8% in 2022 (Kappelman, 2022)². In the Banking and securities sector, the IT budget even reached 10.14% of revenue (Ammara and Al-Faryan, 2023)³. In terms of analytics, the big global data and business analytic market size in 2020 is US\$198.08 billion and is expected to reach more than triple (Kelvin and Mubashar, 2023)⁴

Figure 1 Why Data-Driven Decision Making Is Important

¹ (Gul, 2023)

² (Kappelman, 2022)

³ (Ammara and Al-Faryan, 2023)

⁴ (Kelvin and Mubashar, 2023)

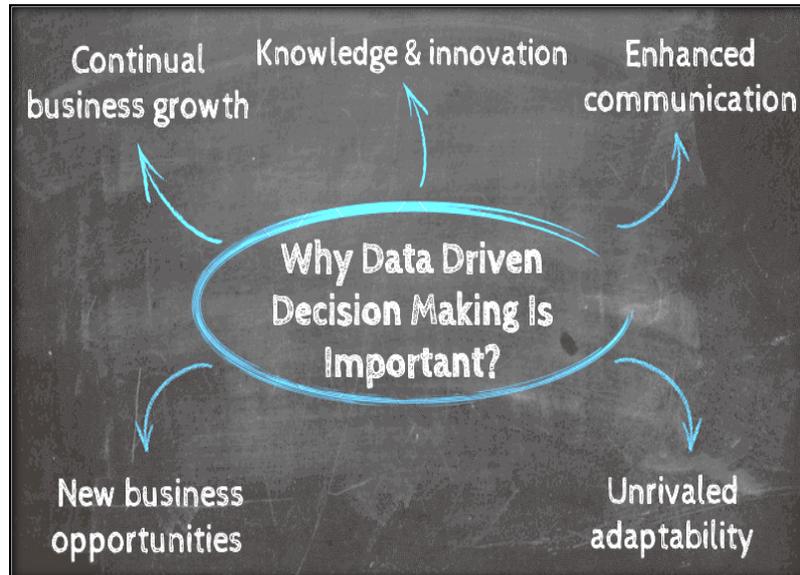


Fig-Source: (Roger, 2022)¹

1.1.5 IT Industry in India

India's technology-driven (IT) economic system has been developed to include various technology and computing fields. By hiring around 10 million people, the Indian IT/ITeS industry significantly contributes to the country's economic prosperity. In 2015-2016, the sector's total revenue was anticipated to rise to over US\$130 billion, accounting for 7.7% of the country's GDP. According to (Mohapatra, 2015), the arena is anticipated

¹ (Roger, 2022)

to grow at 12%–14% in 2016–2017, with annual sales predicted to be threefold employing in 2025. global commercial enterprise Machines (IBM), Dell, Microsoft, and Hewlett-Packard are the most venerable companies inside the Indian IT zone (Pandey, 2011)¹ to boot, and the Indian IT enterprise has performed a tremendous position within the financial enhancement via increasing exports, elevating dwelling standards, and generating cash (Jain M. a., 2014)².

Figure 2 Key segments of the Global IT Market

¹ (Pandey, 2011)

² (Jain M. a., 2014)

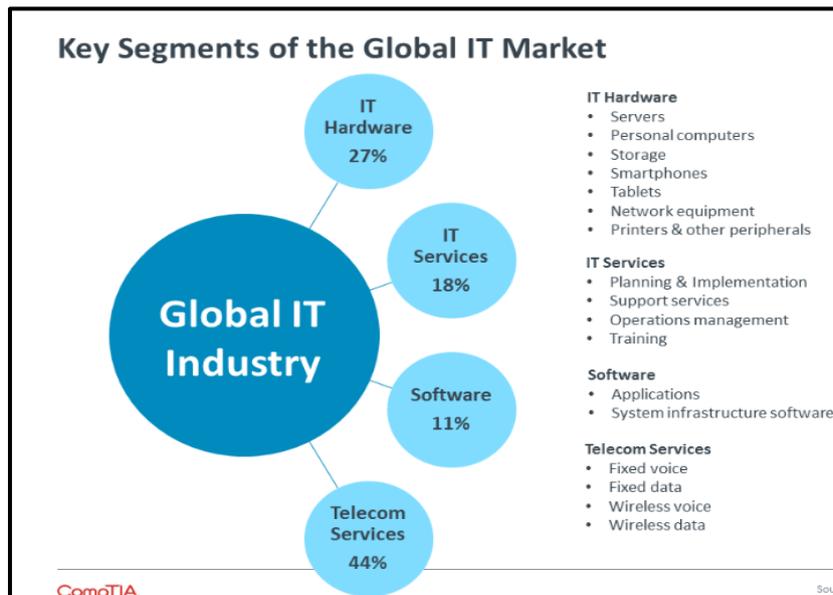


Fig-Source: (Spark, 2015)¹

This study was conducted on how Employee Attrition impacts organizational productivity and how DDDM and Analytics (Zina Cole, 2023)² give insights into employee recruitment, churn prediction, and various retention strategies that play a crucial role in the Indian IT sector. In India, the Information Technology sector predominantly comprises summing it, and these are some critical data related to IT Industry in India:

¹ (Spark, 2015)

² (Zina Cole, 2023)

Figure 3 IT Industry key milestones



Fig-Source: (Swathi Moorthy, 2022)¹

- Export of IT services: 200 billion USD
- Export of Software Products and Engineering Services: 28 Billion USD

¹ (Swathi Moorthy, 2022)

- Export Revenues from the IT industry: 150 Billion USD (Sun, 2022)¹
- Analytics Applications Software Market: 31.6 Million USD
- Growth of Business Intelligence Software Revenues: 14.58%
- Infrastructure Software Market: 2.4 Billion USD
- Size of Public Cloud Services Market: 1.9 Billion USD
- Largest Segment of Public Cloud Services: Infrastructure as a Service (IaaS)
- Direct Employment from IT Industry: 3.9 Million (IMI-Bhubaneshwar, 2023)²

According to the World Economic Society, the capacity to recruit and retain top performers will be the most accurate determinant of a company's long-term sustainability over the next five years (Alsayegh, 2020)³. In some businesses, for example, there is a phenomenon known as "merry-go-round personnel" (Tseng, 2015)⁴ in which individuals hop ship within the industry, and corporations recycle people. It is commonplace for top-level individuals in the IT sector to 'job-hop (Pawar, 2023)⁵. Attrition, in its most basic form, describes the phenomenon in which an employee departs a company.

¹ (Sun, 2022)

² (IMI-Bhubaneshwar, 2023)

³ (Alsayegh, 2020)

⁴ (Tseng, 2015)

⁵ (Pawar, 2023)

Figure 4 IT Sector Rising Attrition Levels

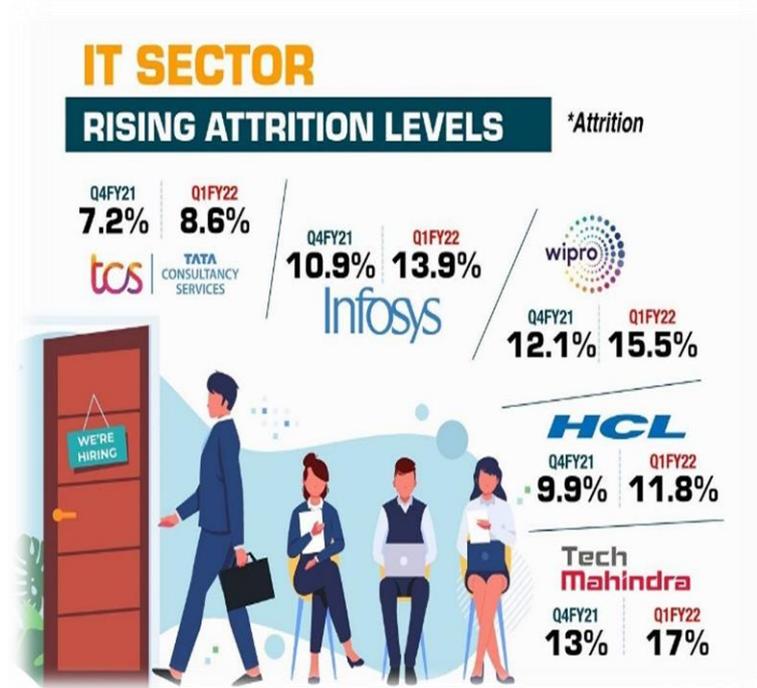


Fig-Source: (Sharma D. , 2021)¹

1.1.6 HR Analytics

¹ (Sharma D. , 2021)

The Progression of HR Analytics Explores how HR analytics has changed over the decades, from basic automation to the digital age, with enormous statistics and artificial intelligence. (Van den Heuvel, 2017)¹. We focus on automated reports, automated integration of resources and projects, automated performance sheets, and automated compensation records with more scope for HR to manage tasks more efficiently by reducing administration tasks (Saxena, 2020)².

Figure 5 Data-Driven Decision Making In HR

¹ (Van den Heuvel, 2017)

² (Saxena, 2020)

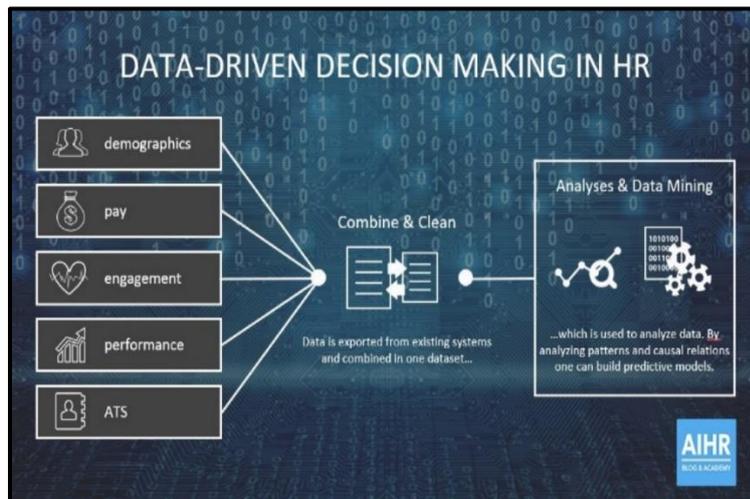


Fig-Source: (Arup Barman, 2018)¹

HR Analytics has the power (Gul, 2023)² to early employee movement prediction and organization. In a large organization, many employees are not working; HR analytical tools or methodologies are very productive for providing a data-driven understanding of what works well and what does not. Organizations can make changes or improvements and plan more effectively for the future. HR Analytics applies various statistical tools to the collected data to create interventions, propose strategies and assess their effectiveness in the organizational performance of multiple departments such as marketing, finance,

¹ (Arup Barman, 2018)

² (Gul, 2023)

and others. Though HR Analytics is not less known but has remained relatively less explored.

Figure 6 Illustrating the usage of various types of people analytics during Time

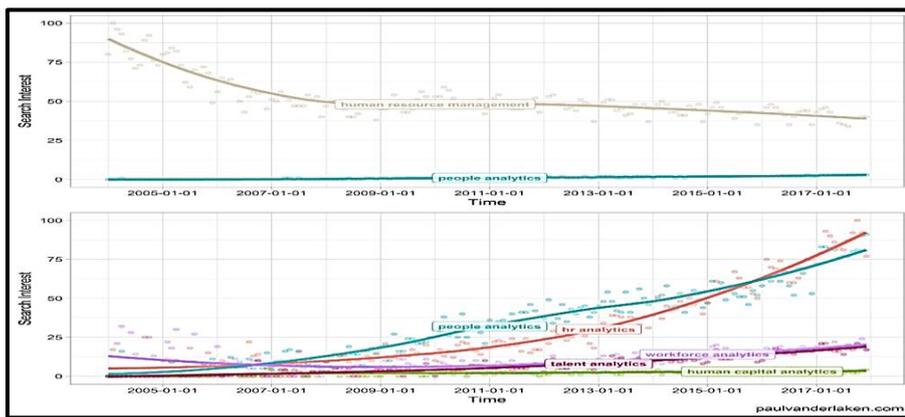


Fig-Source: (Nishith Pawar, 2023)¹

Innovators in people analytics would highlight cutting-edge approaches for recruiting and retaining top talent, which is now employed in advanced businesses (Jada Kameswari, 2023)². People analytics allows researchers to evaluate workforce analysis to assess the current state of the workplace effectively and to advise conversations about

¹ (Nishith Pawar, 2023)

² (Jada Kameswari, 2023)

the skill set designed to reach corporate goals, as well as how statistics and refined investigation applied to individuals' issues like recruitment and selection, performance assessment, command structure, selection and promotion, work environment, remuneration, and collaborative effort. One financial services firm used this knowledge to significantly improve its staff planning process.

1.1.7 Employee Attrition

Employee attrition does not only mean the loss of an employee, but it also reflects the loss of a customer from the organization. Employee attrition is a major problem that causes many companies to incur significant costs to find and hire new personnel or to retain the right candidate. It plays a pivotal role in employees leaving an institution due to lesser satisfaction at the workplace. Significantly impacts the decrease in employees and is seen as a negative sign concerning lower productivity and employee morale. Higher employee rate attrition shows a failure of organizational effectiveness in retaining a qualified employee. The current research study is envisioned with the core objective of investigating the causes of employee churn. The research study uses primary and secondary data on attrition-related aspects to meet the study's aim. This research gives accurate information on employee churn and what retention strategies are crucial in controlling the organization's loss due to employee attrition. We are sure that the organization can attain fulfillment for human beings.

1.2 RESEARCH PROBLEM

1.2.1 Employee Attrition:

The epoch attrition refers to a sluggish, nevertheless painstaking curtailment in crew numbers that crop up as the workforce retires or renounces and are not transposed (Gupta S. S., 2010)¹. Its miles are habitually used to delineate downsizing in an organization's employee pool by human assets (HR) fancier. Only a few folks kick-off and succumb to their careers in a solitary corporation. Plebeians flow on after a time, or the corporation forces them to locomote on with an involuntary termination. Humans leave organizations to resemble a prepossessing honest acknowledgment, yet there is plenty to unpack with employee attrition. Whenever anybody ceases operating for the organization for any purpose and is not changed for an extended period, that would be employee attrition (Klehe, 2011)².

Artisan attrition is phasing an employee who leaves the enterprise beyond any tack, including voluntary resignations, layoffs, failure to locomote back from a fleet of absence, or even infection or loss of life (Thilaka, 2020)³. The cost of turnover in the

¹ (Gupta S. S., 2010)

² (Klehe, 2011)

³ (Thilaka, 2020)

United States is over \$360 billion annually. Recruiting, employing, training, and rewarding new staff are all included in this expense. Employee attrition is also a considerable challenge for many organizations. It has a hefty cost. Employees take their skills and knowledge with them when they leave, and firms often have to pay extra money to replace them.

Furthermore, the loss of knowledge and experience may impact the remaining employees' productivity. People quit their jobs for a multitude of reasons. Some individuals prefer to leave to pursue new opportunities. Some people quit because they do not think they are being treated moderately or are unhappy with their pay and benefits. Some employees leave because they believe they are being forced to do jobs they detest. Some people quit their jobs to create their businesses. Many people quit their jobs because they are dissatisfied with their work or the firm. Attrition is exceptionally high in consistently growing retail, hotel, and finance industries. Since these sectors are volatile, employees are frequently more comfortable leaving employment at the business cycle's peak. Employee turnover can be exceptionally high in specific businesses and geographical areas. Manufacturing, the healthcare industry, and retail (Ponsano, 2013)¹ BPO, Software rely heavily on specific abilities.

¹ (Ponsano, 2013)

Employee attrition is not a new occurrence. Indeed, the United States is thought to have had high levels of employee turnover for nearly 100 years. Monitoring an organization's turnover rates is essential for identifying possible learning and development needs. Increased employee retention can help to reduce employee turnover. Employers prioritize employee retention since employee turnover is costly.

1.2.2 Attrition Types:

There are two cardinal approaches to employee attrition, predominantly

➤ **Voluntary Attrition** (Emadi, 2020)¹:

Voluntary Attrition materializes through employees fleeing independently. Voluntary attrition is, to say nothing of, devastating to employer morale. It can negatively ramifications any paramount employees if their workloads roar. And

➤ **Involuntary attrition:** (El-Rayes, 2020)²

While the corporation concludes to constituent procedure with an employee, that is involuntary attrition. It could be beyond a whereabouts expulsion, for instance, due to

¹ (Emadi, 2020)

² (El-Rayes, 2020)

reorganization or layoffs, for justification (which includes stealing or scrimmage), terrible attainment, or termination phase, a person abandons their occupation.

Figure 7 Employee Attrition Types

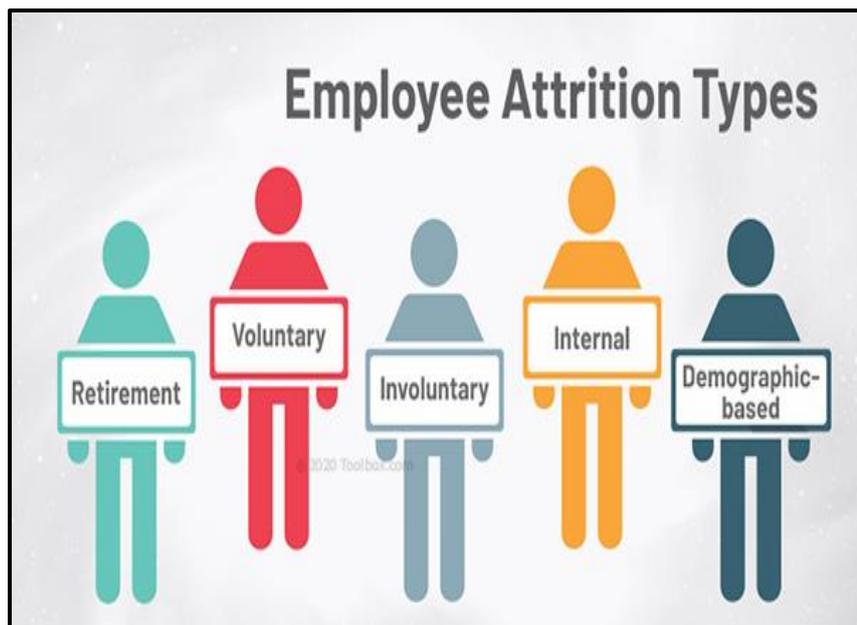


Fig-Source: (BasuMallik, 2021)¹

➤ **Retirement-related attrition**

¹ (BasuMallik, 2021)

If our organization has lost two or three employees this year, this is statistically too small an employee group to consider attrition. However, if a significant portion of our team departs simultaneously, this might result in attrition. Retirement attrition should not be overlooked; our senior professionals may retire early or become independent consultants for reasons other than age.

➤ **Internal turnover**

Employees are resigning from one department to work in another. Internal attrition is sometimes advantageous because it directs talent into more profitable areas. It also guarantees that employees are more suited to their jobs.

➤ **Demographic-based attrition**

It is a significant challenge for progressive businesses attempting to create an equal-opportunities workplace. Employees from a single demographic women, ethnic minorities, individuals with disabilities, veterans, or senior professionals are essentially departing the organization.

We must quickly implement employee surveys to determine the main reason for demographic-based attrition before it impacts our workplace culture. A good culture can serve as an antidote to the smoking pandemic.

However, an investigation is warranted if a given department has seen a significant attrition rate in one year. Is there anything lacking from the job? Is the management underqualified? These are the questions that HR must ask and answer.

The superiority of Artificial Intelligence and HR Analytics ideas inside the HRM discipline could be minimal. HR professionals advocate statistics-driven approaches for analyzing the most vulnerable variables to employee churn among personal, work-related, and salary-related traits that play a critical role in employee retention so that HR departments may make decisive decisions in employee retention.

1.3 PURPOSE OF RESEARCH

1.3.1 Different Purposes

Purpose-1: Employee Attrition Identification

Deliberate or unplanned departures of key personnel can purpose massive losses by way of manner of lack of continuity of employees, training gaps, and absence of know-how, taking prolonged time to fill positions, and if HR is unable to fill with appropriate, skilled human beings result in gaps/ hiring freeze conditions that increase the workload of other employees result in employee burnout circumstance. Employees get demotivated

because of higher workload and misplaced productivity, delayed or ignored deadlines, and hiring expenses of replacements (Singh e. a., 2012)¹.

Purpose-2: Evaluating the influence of turnover initiatives:

Employee Retention Strategies assist organizations in providing effective employee communication to strengthen the commitment and worker support for critical business goals. In contemporary times, corporations take an anticipatory approach to developing retention strategies. Organizations try to improve the work environment by concentrating on employees' morale, motivation, contentment, capacity, and willingness to be highly productive, yet attrition remains high. Every organization has nearly identical retention policies and tactics; however, the effect of these retention factors suggested by the employer varies per organization. As a result, it is critical to analyze and identify the most influential retention variables based on employee expectations.

Purpose 3: Enhance the overall performance of the organization:

➤ **Productivity effect**

¹ (Singh e. a., 2012)

When an employee quits, the organization undoubtedly loses some productivity. When an ex-employee is vacant, diminished productivity affects project deadlines and business income. Even if other team members take on essential jobs, other less important things fall out of place, lowering team productivity and performance.

➤ **Knowledge Loss effect**

A recruit may perform all the activities previously performed by an ex-employee, but do we believe the specialized knowledge and experience remain the same...? No.

There is more to business than just selling a product, creating computer programs, filling out Excel sheets, and managing databases. A successful company organization is built on retaining relationships with current clients, their know-how, and excellent expertise. When an employee leaves, this information is lost. That is why this knowledge and familiarity are more valuable than anything else.

➤ **Training Costs effect**

Training a new employee costs the organization hundreds or thousands of dollars. The training expenditures are absorbed immediately by the firm. It becomes costly when employees fail to take advantage of training opportunities or quit.

1.3.1. Why do people try to switch or leave specific types of organizations?

In this digital age, the \$143-billion Indian IT industry hires more than three million human beings, draws high-quality talent internationally on one side, and suffers from excessive "employee churn /attrition."

Figure 8 Attrition Percentage Over the past Five Quarters

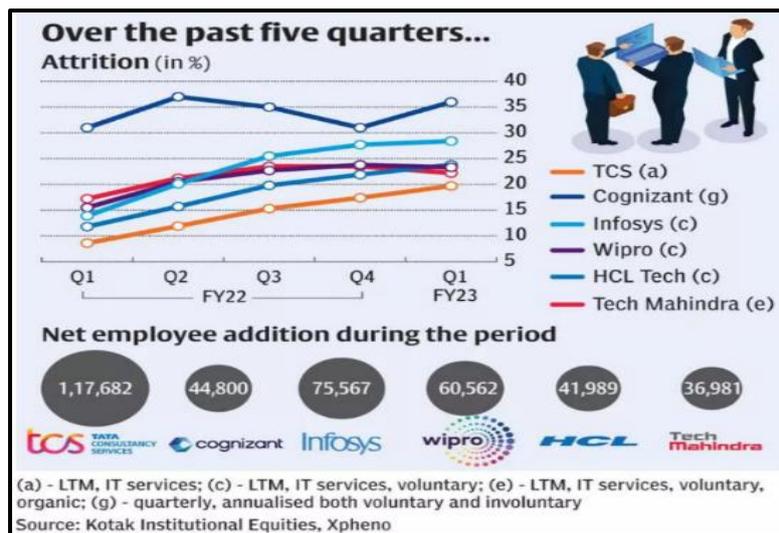


Fig-Source: (Chaturvedi, 2022)¹

Attrition within the IT services phase tiers from 15-18 percent primarily based on marketplace capitalization; the top 3 leading IT companies - TCS, Infosys, and Wipro had been taken for the study (Gupta S. S., 2010)² and the results are INFOSYS-13.60%,

¹ (Chaturvedi, 2022)

² (Gupta S. S., 2010)

TCS-15.50%, and WIPRO -16.10% of Employee Attrition rate. Attrition rates of 19-20% are becoming the norm (Gupta S. S., 2010)¹. Talent Acquisition, Learning & Development, Compensation, Health & Safety, Employee Engagement, Retention, Awards & Recognition are considered while calculating for all three organizations.

1.3.2. Significant/ Common Triggering Attribute for An Employee to Leave the Organization

Figure 9 Drivers of Employee Turnover

¹ (Gupta S. S., 2010)

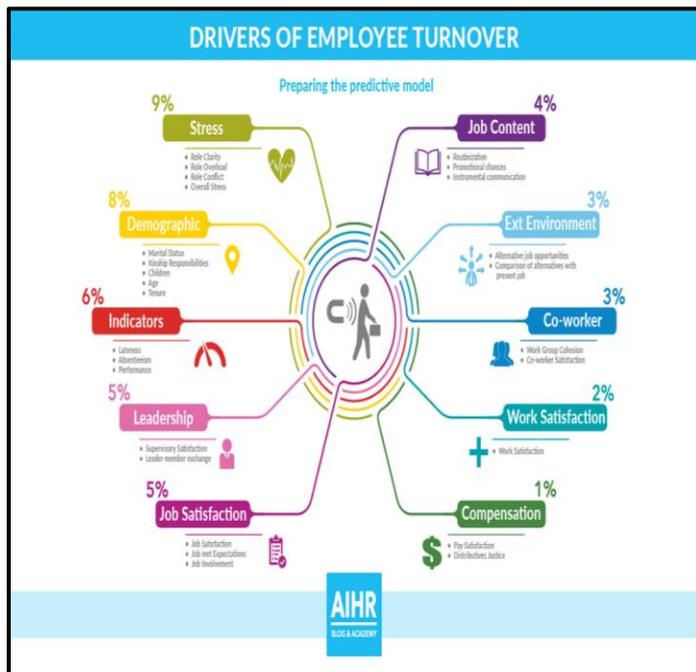


Fig-Source: (Verlinden, 2022)¹

- Recruiting and selecting the incorrect personnel in the location
- Personnel Demographics
- Toxic workplace
- Business Relocation
- Covid-19 Shutdowns

¹ (Verlinden, 2022)

- No/lack of professional boom
- Employee well-being (Heffernan, 2021)¹ (Harney, 2018)²
- No appraisal system for a long period
- Lack of career growth
- Loss of training and development activities

Table 0:1 Feature Description of the Considered Data

Employee Personal Attributes	Employee Work-related Attributes	Employee Salary related Attributes
Age (Singh, 2017) ³ , (Alam 2018) ⁴	Environmental satisfaction (Alam, 2018) ⁵ (Yahia 2021) ⁶	Monthly income/worker's compensation (Mishra 2016) ⁷

¹ (Heffernan, 2021)

² (Harney, 2018)

³ (Singh, 2017)

⁴ (Alam, 2018)

⁵ (Alam, 2018)

⁶ (Yahia, 2021)

⁷ (Mishra, 2016)

Business Travel (Karande, 2019) ¹	Job involvement (Zhao, 2018) ² (Ponnuru 2020) ³	No of the companie worked
Distance from home	Job level	Overtime (Mishra, 2016) ⁴
Education (Singh 2017) ⁵ , (Alam, 2018) ⁶	Relationship satisfactio with peers and superiors (Shah S. a., 2020) (Khera, 2018) ⁸	Percent of salary hike
Gender discrimination/bias	Average monthly hours	Performance rating

¹ (Karande, 2019)

² (Zhao, 2018)

³ (Ponnuru, 2020)

⁴ (Mishra, 2016)

⁵ (Singh, 2017)

⁶ (Alam, 2018)

⁷ (Shah S. a., 2020)

⁸ (Khera, 2018)

Department	No of projects	Stock option level
Marital status (Ponnuru, 2020) ¹	Decision skill possesses	Total working years
Economic status Social status	Work-life balance (Yahia, 2021) ²	Years at company
Willingness to relocate	Job satisfaction (Gao, 2019) ³	Years in current role
People with disabilities	Job involvement (Kirschenbaum, 1999) ⁴	Years since promotion (Alduayj, 2018) ⁵
Children Education	Job performance (Shah S. a., 2020) ⁶	Years with current manager

¹ (Ponnuru, 2020)

² (Yahia, 2021)

³ (Gao, 2019)

⁴ (Kirschenbaum, 1999)

⁵ (Alduayj, 2018)

⁶ (Shah S. a., 2020)

Career growth	Tenure (Ajit, 2016) ¹ , (Colomo-Palacios, 2014) ² , (Mishra, 2016) ³ , (Alduayj, 2018) ⁴ (Kirschenbaum, 1999) ⁵ (Zhao, 2018) ⁶ , (Khera, 2018) ⁷	Awards, Recognition, Employee measures Rewards Bonus welfare (Shah S. a., 2020) (Yahia, 2021) ⁹
Designation hike	Grade (Colomo-Palacios, 2014) ¹⁰	On-time salaries

¹ (Ajit, 2016)

² (Colomo-Palacios, 2014)

³ (Mishra, 2016)

⁴ (Alduayj, 2018)

⁵ (Kirschenbaum, 1999)

⁶ (Zhao, 2018)

⁷ (Khera, 2018)

⁸ (Shah S. a., 2020)

⁹ (Yahia, 2021)

¹⁰ (Colomo-Palacios, 2014)

Attitude towards work	Training (Gao, 2019) ¹ (Ponnuru 2020) ²	Welfare measures
Skill level	Ineffective working practices	Profit-sharing
No of dependents	Hazardous environment	Extra amenities

1.3.3 Significance of Predictive Analysis

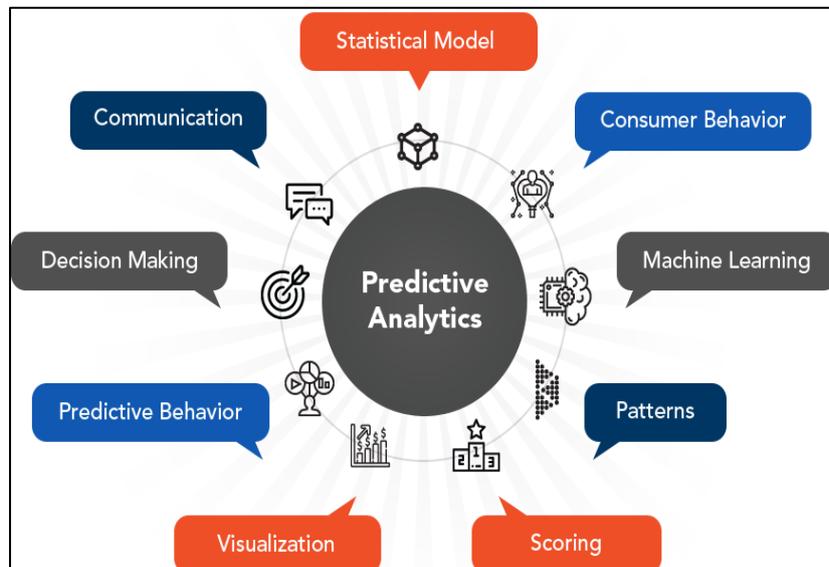
Fundamental issues in every business organization stumble upon the price of Hiring the following incumbent, gearing up duration earlier than the following incumbent, Taking charge & start to deliver, a charge training the following incumbent. Predictive analytics is the practicality of innumerable statistical equipment & plan of action and miniature to forecast how a variable will impulse gist in subsequent and based totally on the inferences the HR be permitted layout a brand-new course of action. Predictive analytics is commonly used in HR to project attrition rates, retention

¹ (Gao, 2019)

² (Ponnuru, 2020)

percentages, overall performance, and productivity and put a number on recruiting. So, it foretells the managers approximately the footprint numerous human beings' guidelines will have on exceptional human beings' troubles. Predictive analytics goes to be the game-changer for incoming instances. (Likhitkar, 2020)¹ (Sharma H. a., 2020)².

Figure 10 Predictive Analytics Use Cases



¹ (Likhitkar, 2020)

² (Sharma H. a., 2020)

Fig-Source: (ainxt, 2023)¹

Predictive models assist organizations in luring, preserving, and developing their most skilled personnel. Many agencies use predictive models to forecast their human capital attrition rate to reduce hiring, training, and transition prices. To perceive employee attrition, Predictive models are maximum beneficial. Through predictive algorithms, organizations have supremacy giant proficiency and can endorse preventive measures for employee attrition. The predictive framework is invigorating throughout an expansion of parameters. At a primitive stage, the version works by clustering/ classifying employee profiles based on numerous attributes.

It generates various periods of endangerment of attrition. Employee Retention and Turnover Intentions Every so often, different parameters like acquisition through the years, pay boost, drudgery batch, and academic organization are also considered. Employee satisfaction relates to a worker's sense of pride in his or her work, earnings, job merchandising, organizational loyalty, and organizational pinpointing collision on employee task delight (Shah N. , 2017)². Employee engagement refers to a worker's

¹ (ainxt, 2023)

² (Shah N. , 2017)

devotion to his or her company. The degree to which a person intends to leave his or her current work is referred to as turnover intentions. Anyhow, the version's accuracy is immediately proportional to the possibility of parameters, which in turn turtle, accompany the cohort of the 'genre' of the predictive version most appropriate for the employer.

1.3.4. Few Advantages Of The Predictive Attrition

Figure 11 Few advantages of Predictive Attrition

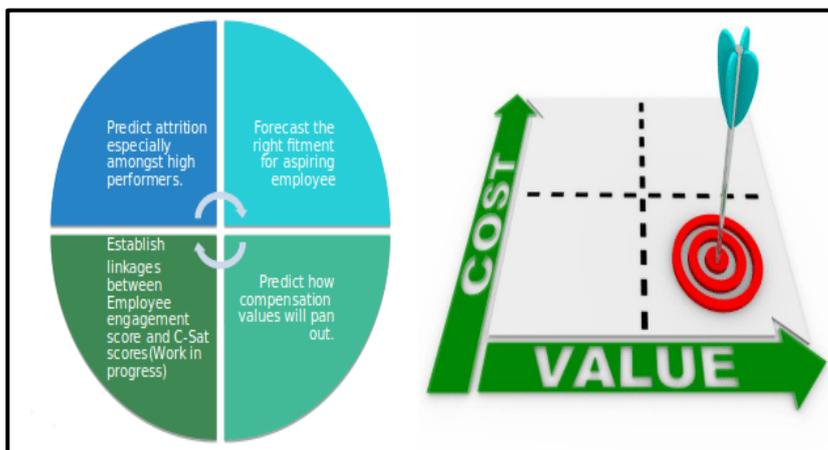


Fig-Source: (Edureka, 2022)¹

¹ (Edureka, 2022)

- Can Identify employee requirements, strengths, and weaknesses
- Gives support to Reduce the charge of the latest proficient acquisition
- Can assess the expertise and skill units, length of monetary and productivity loss due to attrition.
- Provides an exceptional fact of personnel delivery and gets in touch with
- Tremendously masterly situated with contingency plans based predominantly on the insights and foresight furnished to manipulate the predictive version.

1.3.5 Research Purpose

Since April 2021, more than 19 million workers and counting have departed their employment, a record rate that has disrupted businesses worldwide. Companies are straining to solve the issue, and many will continue to suffer for one simple reason: they have no idea why their employees are leaving in the first place. Rather than investigating the true causes of attrition, many companies resort to well-intended quick fixes that fall flat: for example, they increase pay or financial perks, such as offering "thank you" bonuses, without making any effort to strengthen the relational ties people have with their colleagues and their employers. The result? Employees detect a transaction rather than gratitude. This transactional connection reminds them that their actual needs are not being satisfied.

- **Employees.**
-

Employees are exhausted, and many are in mourning. They desire to rediscover and revise their sense of purpose in their employment. They seek social and interpersonal relationships with their co-workers and supervisors. They want to experience a sense of belonging. They want income, benefits, and perks, but they also want to feel appreciated by their organizations and supervisors. They want genuine relationships, not transactions, even if they are not always in person.

Company executives put their firms at risk by failing to comprehend what their people are running from and what they may gravitate towards. Furthermore, because many employers are handling the situation similarly, failing to invest in a more fulfilling employee experience and failing to meet new demands for autonomy and flexibility at work, some employees are choosing to leave traditional forms of full-time employment entirely.

Figure 12 Mc Kinsey’s Great Attrition or Great Resignation



Fig-Source: (Swathi Moorthy, 2022)¹

In this article, we highlight new Mc Kinsey research on the nature and features of the Great Attrition, also known as the Great Resignation, by some, and what is driving it. The simple fact is that the Great Attrition is happening, it is pervasive, and it is likely to continue if not accelerate, and many organizations, despite their best efforts, do not comprehend what is happening. These businesses are making unproductive decisions based on incorrect assumptions.

Companies that seize this unique opportunity may gain an advantage in the fight to attract, develop, and retain talent. This does not have to be the case. Companies that make a determined effort to understand better why people leave and take adequate measures to keep them might turn the Great Attrition into the Great Attraction.

1.3.6 Reason for addressing Employee Attrition Problem as a fundamental research problem:

As academicians, we have observed that many outgoing students change their employers frequently, especially those at the junior level or with less than five years of

¹ (Swathi Moorthy, 2022)

experience. From the employer's perspective, employee attrition poses a significant challenge for the organizations that hire them, as they have to deal with various costs and risks associated with losing and replacing their human capital. These costs and risks include reduced productivity, lower quality of work, loss of knowledge and skills, increased recruitment and training expenses, decreased morale and commitment among the remaining employees, and disruption of teamwork and collaboration. Moreover, employee attrition has become even more prevalent and problematic for many organizations in the current pandemic and economic uncertainty scenario.

Therefore, we are interested in studying the problem of employee attrition and predicting its occurrence based on the behavioral patterns of employees. We want to explore the factors influencing employees' decisions to stay or leave their jobs, such as monetary terms, work-related causes, pandemic effects, bossism, and social and personal attributes. We also want to identify the reasons for employee attrition and suggest appropriate retention strategies to control human capital through data-driven people analytics.

Data-driven people analytics uses data and analytical techniques to understand and improve various aspects of people management, such as hiring, performance, engagement, and retention, diversity. Data-driven people analytics can help HR managers to make informed and evidence-based decisions that can enhance organizational effectiveness and employee well-being. By using data-driven people analytics, HR managers can:

- Identify the patterns and trends of employee attrition and its impact on organizational outcomes.
- Segment the employees into different groups based on their attrition risk and retention potential.
- Understand the drivers and barriers to employee retention and satisfaction
- Develop and implement customized and targeted interventions to reduce employee attrition and increase employee loyalty
- Monitor and evaluate the effectiveness of retention strategies and adjust them as needed
- Communicate and justify the value and benefits of retention strategies to the top management and other stakeholders

By doing so, We hope to provide valuable insights and recommendations for HR managers and policymakers on reducing employee attrition and enhancing employee retention using data-driven people analytics.

1.4 SIGNIFICANCE OF THE STUDY:

Employee attrition analytics is a sort of predictive analytics that may assist organizations in understanding why workers leave willingly, which attribute is making them leave, and how to utilize data to forecast and decrease attrition risk. Employee

attrition is the natural process through which people leave their jobs for personal or professional reasons. Employee attrition analytics may calculate the attrition rate by measuring the number of exits within a specific sector and time. It may also detect indicators and risk factors for employee discontent and attrition. Employee attrition analytics is critical for keeping top employees, particularly in light of the COVID-19 epidemic and the development of remote work.

1.5 RESEARCH GOALS, QUESTIONS, & OUTCOMES

1.5.1 Research Goal

This thesis aims to give the organization a model that will aid the HR department in identifying at-risk personnel. This model is trained using historical employee data and is retrained whenever new data is available. When the model identifies an employee at risk of leaving the organization, the HR department and the person's supervisor should be notified. The model should also provide the most likely reasons for this employee's departure to aid the HR department. These reasons might be utilized to develop a customized intervention for the identified situation. The HR department/supervisor can utilize these traits as criteria for where to place employees.

The model should identify and rank the essential features contributing to turnover classification. The HR department/supervisor can use these characteristics as recommendations to determine their possible action. For example, if overwork is

identified as a cause of turnover, the HR department/supervisor can investigate the sources of this overwork and then strive to minimize these causes.

1.5.2 Research Questions:

- Can We Predict Employee Attrition Through Employee behavioral patterns Advancement Using BI Tools?
 - What are the retention strategies playing a pivotal role in terms of retaining the skilled professional?
 - Finding out the various reasons for employee churn
 - Identify the impulsive factors which determine employee attrition
 - Elevate Significant after-effects due to employee attrition
 - Analyze employees satisfied with their pay for the job role
 - Assess employees who feel overworked and micromanaged.
 - Evaluate on employee receives training, new opportunities, and growth prospects within the organization.
 - Identify whether the company work culture aligns with the employee's values and does the boss give room to grow.
 - Discuss with employees on their expectations in the post-pandemic era from their employer.
 - Evaluate the organization's offers to the resigned employees if he/she consents to continue their services.
-

- Identify the correlation between the considered data attributes
- Dept, age, pay scale, job satisfaction, and training attributes impact employee churn.

1.5.3 Benefits Or Impacts Of Our Goals:

The data-driven human resources department is centered on people analytics. People's decisions in organizations today are primarily analytical and data-driven, and having and utilizing well-functioning people analytics is critical to winning the fight.

- **Making data-driven decisions and adhering to evidence-based hiring practices:**

HR may make evidence-based judgments rather than trusting their gut instinct by analyzing internal data, research, and studies, as well as expert decision-making, experience, values, and concerns. This allows for getting rid of biases, interim remedies, and inconsistencies. Organizations may use data to increase recruiting speed by 80% while lowering the attrition rate by up to 50%.

- **Employee and organizational performance has improved:**

Dashboards and trends demonstrating specific issues, such as interaction, job stress, multiculturalism and inclusion, and occupational danger assessments, all boost performance. Practically increased employee production resulting in improved effectiveness in some cases.

- **Enhance employee Turnover:**
-

Hired hand churn (ECn) is an exuberant unease for any consortium that adversely ramifications its typical bunce and trademark (Jain N. a., 2021)¹. When employees quit the organization, there may often be no factual information about why. There may be collected reports or statistics on man or woman situations, but no way of knowing whether there is an overarching cause or trend for employee attrition. With turnover being costly in terms of misplaced time and income, organizations need this perception to save the turnover from becoming an ongoing problem (Setiawan, 2020)²

- Can acquire and examine beyond records on turnover to perceive trends and patterns indicating why personnel stops.
- Collect data on worker behavior, including productivity and engagement, to better recognize the reputation of present-day employees.
- Can Correlate both sorts of facts to recognize the factors that cause turnover (Fallucchi, 2020)³.
- Can become aware of patterns of employee engagement, worker pride, and overall performance.

¹ (Jain N. a., 2021)

² (Setiawan, 2020)

³ (Fallucchi, 2020)

➤ **Enhancing employee satisfaction:**

Employee satisfaction refers to the pleasure employees feel as members of your organization. Managing attrition well may favorably influence their impression of the organization. We might concentrate on how to appeal to their principles and offer the benefits of continuing within their current positions. Employees can also be encouraged because their peers opted to stay with the company, reinforcing their perception that it is a good workplace.

➤ **Recruiting skilled professionals:**

Another benefit of attrition management is that it improves our recruitment process. Increased employee satisfaction can help our company build a strong standing in the market. If talented applicants are looking for work, they may be interested in joining our team. Employ experienced people that can deliver positive outcomes for our firm. When more employees apply for open positions, we may have more possibilities to select from various applicants.

➤ **Boosting employee retention:**

Minimizing attrition can help employees stay longer and continue to support our agency's operations. Employee retention assesses a company's capacity to keep the same employees on the payroll for a lengthy period. A high retention rate may imply that professionals appreciate working for the organization because they have been there for a long time. Organizations might want to avoid committing to and sponsoring costly, time-

consuming hiring initiatives. Their present members may also be committed to attaining development and reaching objectives.

➤ **Create a pleasant working atmosphere:**

The work environment is the location where employees carry out their duties. When the weather is nice, professionals may be motivated to come to work, interact with their co-workers, and produce high-quality results. Create an environment where employees feel at ease and motivated to develop new ideas. We can, for example, design open floor layouts to make managers more approachable and foster cooperation with peers.

Aside from the physical architecture, consider our team's personality compatibility. Some workers may conduct themselves autonomously, allowing them to focus more on their tasks. Others may thrive when they are surrounded by others who share their values. The more appealing the surroundings. Create an environment that encourages mental and physical wellness while maintaining productivity.

➤ **Appoint qualified leaders:**

Leadership may have a significant effect on the experiences workers have while working for a company. If they believe their supervisors support them and provide flexibility, they may choose to extend their contracts. Appoint supervisors who can build genuine relationships with colleagues and positively influence the agency. When making recruiting judgments, evaluate the candidates' communication skills and emotional intelligence.

➤ **Allow employees to be innovative:**

Creative freedom is the flexibility to accomplish our occupational responsibilities as we see fit. Each of our workers may come from a diverse educational and professional background, influencing how they approach their tasks. Think about allowing them to utilize their tactics rather than forcing them to comply with the company's standards. As a boss, we may offer direction when required, but being adaptable can excite staff about their initiatives. The outcomes may be more imaginative, and we may control attrition by demonstrating to associates that we trust their judgment.

➤ **Make professional development a top priority:**

Professional development enables employees to become more adept in their positions as their careers progress. Allow staff to expand their skill set. They may think their employer takes pride in their success, reinforcing the perception that our organization is a good workplace.

CHAPTER II

REVIEW OF LITERATURE

2.1 THEORETICAL FRAMEWORK

2.1.1 PEOPLE-ANALYTICS - Attrition Hassle In The Indian IT Industry

Using digital technologies to create business value has generated enormous data, and using data in decision-making is vital. Although there is growing empirical evidence in favor of a positive association between informed decision-making and firm performance in developed countries, there is little to no evidence of a large-scale study in an emerging economic context. Moreover, there has been scant empirical evidence on how DDDM affects Talent Acquisition, Employee Attrition, Retention, and productivity in the IT sector of developing countries.

Even though HR has much information on their employees, it would be raw data without analytics. It might be thousands of people in a vast organization, and raw data alone cannot detect problems or give solutions.

HR analytics use data-backed evidence and trends to assist HR in understanding the reasons behind what is occurring in the firm, such as overall well-being, employee engagement, and the amount of training each team has received.

Figure 13 Types of Analytics

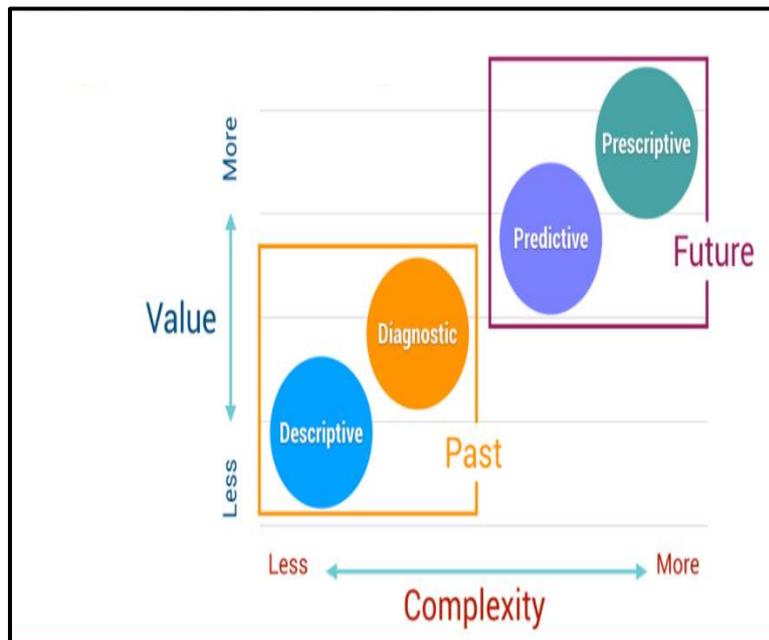


Fig-Source: (Tmarch, 2020)¹

- **Descriptive analytics**, consisting of observations and reports, are significant since they include watching the workplace to understand what is happening early.
- **Diagnostic analytics** takes observations to the next level to determine why and what is causing them. It may be evident that employees are dissatisfied, but it is critical to determine why.
- **Predictive analytics** used less frequently than others; however, it is where organizations can foresee and try to improve their condition.

¹ (Tmarch, 2020)

- **Prescriptive analytics** is the final phase, in which the data used to prescribe what needs to be done to cure the problem. Prescriptive analytics relies on the other three types of analytics to achieve the most outstanding results.

In today's knowledge-driven industry, where people are the most vital human capital assets, employee attrition and potential absconding are massive business problems.

2.1.2 What Exactly Is Employee Attrition

Employee attrition refers to workers leaving a company voluntarily or involuntarily without being immediately replaced. Sometimes employee attrition is due to a hiring freeze; at other times, more profound issues are at play. However, whatever the cause of employee attrition, there is one inevitable result: the company's workforce shrinks in size.

Attrition is a multifaceted problem with many facets. On the surface, it looks like a simple role mismatch. Employees will remain productive if they receive ongoing reminders of their significance to the system.

2.1.3 How to Determine the Attrition Rate

We should monitor the attrition rate regularly to avoid losing more personnel than necessary. (Sometimes, corporations desire less staff; therefore, they seek out high attrition rates.)

The attrition rate calculates using the following formula:

Attrition Formula:

AttritionRate:

$$\frac{\text{Number of Employees that left the workforce}}{\text{Average Number of Employees}}$$

2.1.4 What exactly is Employee Retention

Employee retention occurs when a company can maintain skilled people while reducing turnover. Retention becomes more critical at high company and talent turnover (such as the Great Resignation). An employer's practices, policies, and strategies must work together to retain employees.

Tracking employee retention metrics is critical for retaining competent individuals. This personnel is vital to our company's success, and keeping them should be a top concern for any company. Understanding our staff retention rate allows us to identify what makes the company an extraordinary workplace.

2.1.5 How to Determine the Retention Rate

Employee Retention Formula:

= (Total employees – Employees that left)

Total Employees **X 100 = Retention Rate %**

2.1.6 Employee Turnover vs. Employee Attrition

Figure 14 Employee Turnover vs. Employee Attrition

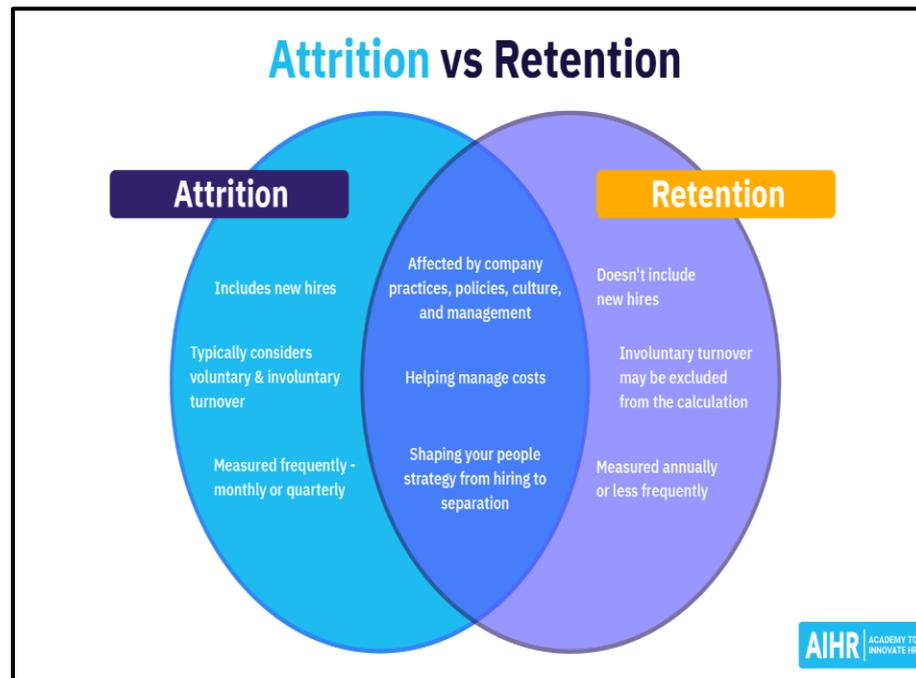


Fig-Source: (Vulpen, 2022)¹

While many use both phrases interchangeably, the fundamental distinction is that turnover includes all terminations, including refilled jobs. Attrition considers long-term vacancies or complete position eliminations.

The company's revenue decreases if the rate of attrition is high. One may have a high turnover rate while running a steady or expanding business. Restaurants and retail, for example, sometimes have significant turnover rates, even as the firm increases.

¹ (Vulpen, 2022)

2.1.7 Attrition Impacts

- It is reasonable to deduce that the organization's ability to adopt an effective human resource policy has failed.
- A chronic loop of productivity loss owing to a lack of personnel pushes additional current employees to work harder, resulting in a work-life imbalance and increased attrition.
- The expenditure on replacing employees is exorbitant.
- Inexperienced Staff
- Employee Burnout
- Employee Turnover
- Lower Productivity
- Unhappy Customers/clients
- Massive loss occurs to the organization regarding man, money, machinery, material, and time.

2.1.8 How attrition impacts an Organization in the long run

It can have several negative impacts on a company in the long run, such as:

- **Lowering morale:** When employees see their colleagues leaving, they may feel less motivated, engaged, and loyal to the company. They may also question their own career prospects and satisfaction.
 - **Reducing productivity:** Employee attrition can disrupt the workflow and performance of the remaining employees. They may have to take on additional tasks or responsibilities,
-

which can increase their workload and stress levels. They may also have to spend time and effort to train new hires or adjust to new team dynamics.

- **Negatively impacting company culture:** Employee attrition can erode employees' sense of belonging and trust. It can also affect the diversity and inclusion of the workforce, especially if specific demographics are more likely to leave than others.
- **Incurring high costs:** Employee attrition can result in significant financial losses for the company. These include the cost of recruiting, hiring, onboarding, and training new employees and the cost of lost productivity, knowledge, and customer relationships.

To prevent these issues, companies need to manage attrition effectively. It can involve identifying the causes and risks of attrition, conducting exit interviews, improving employee retention strategies, and measuring the attrition rate.

2.1.9 Few Theories That Explain Employee Attrition Are

- **Expectancy theory:** suggests that employees' decisions to stay or leave their jobs depend on their expectations of the outcomes and rewards associated with their performance and
-

effort. Employees are more likely to leave their jobs if they perceive their work is not valued, recognized, or rewarded by their organization or supervisor (Win, 2023)¹.

- **Equity theory:** proposes that employees' satisfaction and commitment to their jobs are influenced by their perceptions of fairness and justice in their work environment⁴. Employees are more likely to leave their jobs if they feel underpaid, overworked, or mistreated than their co-workers or employees in similar positions (Balkin, 2023)².
- **Social exchange theory** posits that employees' relationships with their organization and its members based on mutually exchanging benefits and obligations. Employees are more likely to stay in their jobs if they receive positive and supportive treatment from their organization and its members, such as trust, respect, feedback, and recognition. Conversely, employees are more likely to leave their jobs if they experience negative and unsupportive treatment, such as conflict, abuse, neglect, or exploitation (Jain P. K., 2020)³

We do not have to rely on impulsive feelings, thanks to human analytics. Aesthetics allows Human Resource experts it designs evidence-propel alternatives. In the

¹ (Win, 2023))

² **Balkin, 2023**

³ (Jain P. K., 2020)

bargain, analytics empower checking the effectiveness of HR synchronization and exceptional interventions.

DDDM-HR analytics innovators showcase cutting-edge ways of recruiting and keeping top personnel and how these ideas are used in cutting-edge organizations. People analytics allows researchers to evaluate workforce analysis to assess the current state of the workplace effectively and to advise conversations about the skill set designed to reach corporate goals, as well as how statistics and refined investigation applied to individuals' issues like recruitment and selection, performance assessment, command structure, selection and promotion, work environment, remuneration, and collaborative effort. One financial services firm used this knowledge to significantly improve its staff planning process.

Computational modeling aids HR managers in anticipating attrition rates and employee behavior affected by hiring procedures for job possibilities (Biswas, 2023)¹. Success Stories in HR Analytics - HR Analytics is now extensively employed and used in various techniques to offer insightful information.

¹ (Biswas, 2023)

2.1.10 Recent Trends in people analytics with DDDM

Businesses are grappling with issues such as diversity and inclusion, performance evaluation, strategy development, and talent development. The progressive mainstreaming of people analytics is an essential people analytics trend for 2021.

Trends in People Analytics -2021 (Sharma H. a., 2020)¹

Figure 15 Represents the various names in usage for the HR Analytics term.

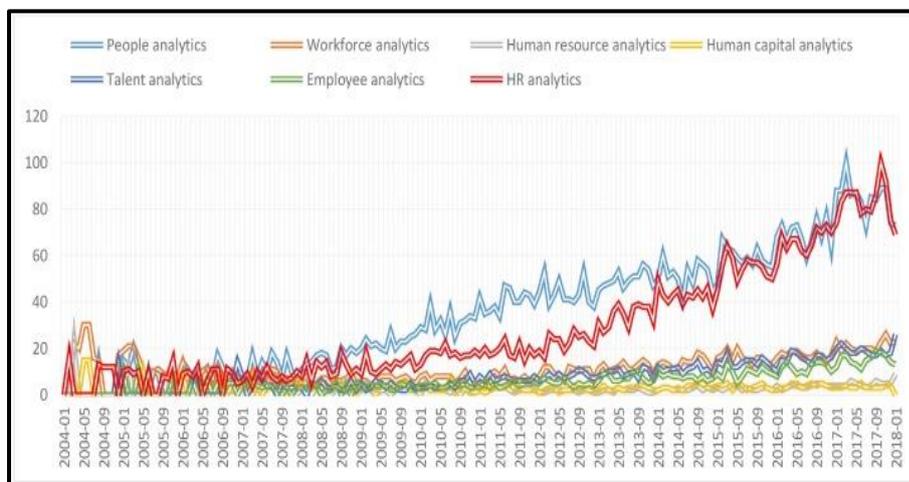


Fig-Source: (Tursunbayeva, 2018)²

¹ (Sharma H. a., 2020)

² (Tursunbayeva, 2018)

Employee retention advantages come from an absence of inspiration in the workforce. Long-term retention demands were autonomous and inclusive tactics.

2.2 THEORY OF REASONED ACTION

2.2.1 Employee Retention Does Influence An Information Technology Company's Overall Success

The most significant loss for the company is the churn rate, which occurs when employees leave, resulting in significant overhead expenses. These costs include the put price of recruiting replacements, the cost of training and developing recruits, the squandering of production due to experienced employees leaving, and the loss of morale in the business ((Cascio, 2010)¹; (O'Connell & Kung, 2007)²). In addition, new personnel must undergo intensive training, which consumes a lot of time and assets for the firm. Low performance now afflicts organizations because staff cannot match customers' requirements without fully understanding the company's method (Bapna, 2013)³. When low-skilled personnel quit, however, overall firm productivity rises, even though a high

¹ (Cascio, 2010)

² (O'Connell & Kung, 2007)

³ (Bapna, 2013)

attrition rate might imply a bad IT sector performance ((Shanmugam, 2016)¹). Client experience is also influenced by personnel, with trained and skilled staff leading to higher satisfaction levels, whereas freshly hired personnel might not be capable of doing so (Kamalanabhan, 2009)². It demonstrates that excessive hand-hired turnover instantaneously affects enterprise productiveness, considering patron desires might not handle appropriately.

2.2.2 Six Significant Variables In Employee Retention

According to research, it includes people and culture, workplace recognition, meaningful benefits, continuing training, working environment, and purpose and values alignment. By making data storage about employee traits, behavior, and effectiveness more accessible, explicable, and practical, DDDM-HR-A guarantees to assist establishments higher apprehend their personnel Individually, as a division, or as a variable job. However, as a whole (Pape, 2016)³, this comprises data management,

¹ (Shanmugam, 2016)

² (Kamalanabhan, 2009)

³ (Pape, 2016)

visualization techniques, and predictive modeling, all backed up by personnel assessment and performance metrics. (Guenole, 2017)¹; (Fink, 2017)²)

According to (Das, 2013)³, a set of proper retention methods must be implemented in order to retain competent individuals. Employees must consider always distinguishing lucrative assets and operating as the company's non-depreciating asset. Skilled personnel is an asset that pays off every time. Employee retention is critical for every organization. Adopting retention techniques helps organizations stay competitive. Various models are advantageous for the organization's survival in the market. According to Anitha (2014), researchers have related employee turnover with recruiting sources. They are less concerned about retaining talented staff. Employees run the organization, yet organizations sometimes fail to treat them well.

Other organizations in the market are attracting employees from the IT business. Competing corporations are eager to recruit and hire personnel from other

¹ (Guenole, 2017)

² (Fink, 2017)

³ (Das, 2013)

organizations. The competitive organization provides a better package and policies to recruit the finest competent staff. High pay, technical training, and other incentives all have a role in retaining personnel. According to (Kim, 2005), a firm can only achieve its goals efficiently if it can retain its most talented and competent employees. (M. Thyagaraju, 2023)¹.

Earnings and compensation are cognitively complicated and diverse aspects of work satisfaction. The amount of financial reward an individual receives and the extent to which such remuneration would consider equitable because paychecks help individuals meet their fundamental requirements and help employees meet their higher-level wants. With that job satisfaction, employees can retain for longer.

2.3 HUMAN SOCIETY THEORIES / VARIOUS THEORIES APPLIED IN VARIOUS ORGANIZATIONS

2.3.1 Google

By way of HR analytics, Google has been capable of unconditionally reinventing HR inside its business enterprise.

¹ (M. Thyagaraju, 2023)

DDDM is now extensively employed and used in various methods to provide great information. One example is Google, which used its insights and statistics capabilities to manage employees throughout the interview. The interview questions were automated and adjusted correctly in the way that they have been redesigned and investigated by studying the candidate's profile and applicable level to discover the exceptional amongst all individuals who had implemented and had been taken into consideration suitable potentialities. Google HR specialists now emphasize refining the blend of human and automated jobs to provide a simple, smooth, and transparent work environment. It allows them to give more attention to creativity, intellect, and empathy to give a better applicant and employee experience (Achhab, 2022)¹. Google additionally hired HR Analytics to decide the possibility of an employee resigning from the organization using HR superior analytics and found that those who did not get a promotion within the first four years were likelier to depart the organization. High-quality forecasts save consequences based on worker involvement conduct for each year using HR analytics, estimating that a 0.1 percentage growth in the worker engagement group will significantly increase consumer spending by \$100,000.

2.3.2 Hewlett-Packard (HP)

¹ (Achhab, 2022)

Additionally, it implemented HR data analytics to predict if an employee will depart, which they dubbed the "Flight threat rating. "They accept that extra wages, promotions, and overall performance rankings are all negatively related and that everyone who has obtained a promotion but no longer a salary growth will probably depart the organization quickly. A recent advancement is only beneficial when the lives of ordinary people are better, whether in health, education, employment, the environment, equality, or justice. Establishing good jobs is a critical facilitator for promoting long-term development, economic growth, social welfare, and environmental sustainability (Wong, 2021)¹.

2.3.3 Juniper's Network

People management initiatives focus on putting the right skills in the right places to help the company achieve its objectives. (Boudreau, 2015)² The head of Juniper is looking for more significant concepts and fundamental principles. The team members work together to address problems, even if they do not appear to be HR issues or are too challenging to tackle. HR needed to figure out how Juniper Network's programs and actions could result in a talent pool that was better prepared and empowered to compete

¹ (Wong, 2021)

² (Boudreau, 2015)

with a firm willing to put 10x money at it, which meant that the department needed to innovate. Juniper Networks' strategy was to have one-on-one discussions with each of the company's senior executives, including 100 other managers worldwide, including the chairman.

2.3.4 Wal-Mart

Walmart turned into investigated to peer if there has been a hyperlink between the employer's modern-day commercial enterprise method and its destiny turnover price. The situation was executed by figuring out Walmart's commercial enterprise approach and how it might affect Walmart's future fulfillment if the plan has been to exchange to increase workforce morale. Many companies' Human resources departments have used attrition rate, or turnover, as a vital evaluation aspect. An excessive turnover rate can result in preconceptions approximately an organization's recognition. The Human sources Recruitment (Bhanot, 2022)}¹ and Retention crew process assesses turnover rates and ensures that the corporation's and people's reputations are maintained.

Walmart fails to offer ladies factual probabilities. Walmart's lady employees disproportionately represent low-paying jobs. In 2015, guys made up most people of

¹ (Bhanot, 2022)}

Walmart managers and officers inside the United States of America, despite the truth that women make up 56 percent of the company's US personnel.

Walmart's profit margins are shrinking universally. Walmart's earnings margins, or the ratio of income to cost, had been moderately steady from October 2005 to April 2017, with a maximum of 3.89 % and a minimum of 2.81 % (Walmart, 2018). Conversely, between April 2017 and October 2018, the profit margin declined. By way of 1.78 percent, they were reducing it to 1.01 percent, consistent with RIT news. Walmart personnel are underpaid because they may be unable to maintain themselves and live well. Walmart has overlooked their employees and any behavioral worries because of having cost management (McMann, 2019)¹.

2.4 CONSIDERED DATA POINTS AND THE USE OF DDDM AND PEOPLE ANALYTICS IN THE HR SECTOR TO ADDRESS EMPLOYEE ATTRITION FOR ANALYSIS AND RESULTS BY VARIOUS TOP COMPANIES

(Sharma H. a., 2020)²

¹ (McMann, 2019)

² (Sharma H. a., 2020)

2.4.1 Google's DNA/ Project Oxygen Model

Google's DNA is innovation, and they were the first to use proactive and predicted analytics in HR to explore employee performance, performance evaluation, and talent management (Afzal, 2022)¹, among other things. Google's People Analytics team has created an 8-step process based on their expertise. "Project Oxygen" is a layer research initiative. This initiative created to analyze Google managers' behavior, different traits that set them aside from their competition, and the techniques for preparing them for future roles. This study is also sponsored with the aid of quantitative facts. Internal employee surveys and dashboards such as Likely Turnover Rates, Encrypted Job Evaluation, Survey data, Progress Reports, Advancement & Payment Records, User Feedback, and Hours Served in Joint Efforts uses to collect data. Various analytical models, such as the Retention Algorithm, Project Aristotle, and Predictive Modelling, were applied for the analysis.

2.4.2 Hewlett-Packard's Significant Turnover Model

Significant turnover (Yee, 2022)² in any institution means high hiring costs and Hewlett-Packard (HP) was no exception. Using advanced analytics to create an in-house

¹ (Afzal, 2022)

² (Yee, 2022)

analytical tool called "Flight Risk Program," they allocated specific ratings to HP 300,000+ personnel called Flight Risk Scores and individuals with higher ratings anticipated to give up the organization soon. The HR analytics team collaborated with two data scientists to create the Flight Risk program, which designates specific ratings to workers depending on multiple survey data and anticipates which staff are most inclined to move, allowing the HR team to tailor retention programs to the needs of those staff. The information gathered from various polls on pay raises, advancements (position and rank elevation), job assessments, and internal mobility.

2.4.3 Xerox Corporation Statistics Evaluation- Recruiting Technique

Xerox Corporation sought to save money by employing people analytics. Thus they began the usage of statistics evaluation outcomes within the recruiting technique to decrease their operational expenses, which had been more or less \$5,000 in keeping with new hires: Employee personality assessment tests (Robb, 2022)¹ provided the data, which divided into several categories based on the staff's prior experience, longevity in the corporation, job profiles, and peer group performance evaluations. They depended on automated processes and Evolve Inc.'s Business Intelligence Software for the analysis.

¹ (Robb, 2022)

2.4.4 Genpact's FLM Surveys & Overall Performance Rankings

Genpact is a well-known name in the value-adding market, and it was one of the first to place a premium on people analytics and use the data to develop staff retention tactics (Sharma H. a., 2020)¹. They analyzed hand-hired facts from a ramification of resources, consisting of biographical statistics approximately personnel, work overall performance records, reward machine, and facts from First Line supervisor Surveys (FLM surveys). For the analysis, they created Own People Analytics Recruitment Technology, and to collect the data, they created FLM questionnaires and an effectiveness point system. It changed into created to accumulate management rankings from subordinates.

2.4.5 Nestlé's "Minitab"

Nestlé's employee engagement adventure accelerated with the appointment of Mr. Jordan Pettman (Global Head, People Analytics & Planning). The company's higher turnover rate was a wake-up call to take bold measures accurately. To learn why individuals are not staying with the organization, various reasons, and how to handle the circumstance. To deal with the dilemma, they used predictive analytics and Minitab, one of the crucial statistical software vendors. SAP tools use to collect data, and MINITAB

¹ (Sharma H. a., 2020)

was used to analyze the results. Many variables, such as salary information, personnel records, recruitment sheets, continuity charts, and recognition awards, were evaluated for data collection and analysis.

To determine the employee churn profile, Predictive analytics usage happened to distinguish a correlation between turnover rates and employee qualities.

2.4.6 Sysco's "Personnel Evaluation"

Among the globe's most incredible food service vendors, Sysco has 320 distribution centers with 69000 employees serving about 650000 clients during the arena. Sysco became a forerunner in analyzing human capital funding and its impact on the enterprise's overall performance. They have been capable of setting up a hyperlink among the following traits as a result of their studies: work environment & delight of personnel productivity and staff retention (Bhayani, 2023)¹.

The group's overall performance tracker was created by way of Sysco using predictive analytics. More definitive studies have enabled them to set up, quantify, and track seven critical components of the administrative center: the front-line employee performance, performance, and fashionable of dwelling. There are numerous employee pleasure ratings primarily based on which they could examine personnel performance,

¹ (Bhayani, 2023)

profitability tiers regarding the universal range of devices furnished to the purchaser, and retention.

2.4.7 Mindtree "Turnover Modeling"

Mindtree is a leading worldwide consulting and affords a range of offerings that use Predictive Analytics technologies to examine and evaluate the business enterprise's statistics and talent components and forecast and control personnel attrition. Turnover Modelling (Opatha, 2021)¹: The in-house advanced analytics tools intend to forecast staff turnover by cadre and department.

ABC Risk Model: Regression analysis is use to decide the wide variety of days/hours spent on a process employing employees, the frequency of a job, and the same link with the employee's career ambitions. ABC models classify high performers into three risks identified based on data analysis: High, Medium, and Low.

2.4.8 Marico Kaya Ltd- Integrated HR and Predictive Analytics

Marico Kaya Ltd invests in skincare clinics and is now known as Kaya Ltd; she owned and has successfully integrated HR and predictive analytics into the business with significant benefits. Employee conduct at work, individual employee incentive earnings,

¹ (Opatha, 2021)

and employee success in various roles assigned to them are all characteristics evaluated in the study.

Regression analysis establishes a correlation between the many factors contributing to attrition.

2.4.9 Nielsen's "Predictive Risk Model"

Mr. Piyush Mathur, Sr. vice president of Nielsen's global Analytics organization, commenced the Nielsen human beings Analytics adventure (2016) (Errata, 2016)¹. He invested in setting up Nielsen's people Analytics feature that allows us to maximize the value of the enterprise's most treasured asset: its people. The in-residence people Analytics crew created the Predictive hazard model for amassing and analyzing the statistics. They had been capable of predicting the final results. For the evaluation, the crew took into consideration 20 primary variables, which include worker age, gender, tenure, and worker rankings, amongst others, and to make the version extra concrete, the crew introduced almost 120 more significant variables together with the control period, employee journey time, vacation time, and engagement in CSR activities, amongst others.

2.4.10 Walmart's "Analytics Engine."

¹ (Errata, 2016)

Walmart is a retail behemoth with nearly 2.2 million employees globally, and unplanned attrition costs millions. As a result, they intended to employ people analytics to manage the organization's attrition rate. They gathered and consolidated qualitative and quantitative data from the HR and Finance departments, as well as consumer insights, to gain a better understanding of the company's values.

2.4.11 Infosys's Advanced Analytics

Infosys, a prominent Indian consulting firm, has developed an Advanced People Analytics platform that helps them predict staff turnover and devise employee engagement using various algorithms. Various data points were evaluated in this study, including employee job and performance patterns, remuneration provided to employees, quality performance, attributes of high performers, employee tenure in the organization, employee knowledge and competencies, delays in promotion and career progression, and so on. The team used advanced analytics, AI, and machine learning methods to anticipate the preliminary list of employees who may quit.

2.4.12 Capgemini's "Common HR Dashboard"

Capgemini is a French-based global technology consulting organization. It employs about 2,70,000 people in 50 countries. They wanted to use HR insights to keep their finest people while enhancing employee productivity and business performance. They collaborated with Qlik to construct an application focusing on three main areas:

attrition, talent, and learning & development, and they used Oracle HR System to collect the data. Talent management and attrition are two of the nine separate categories the data has separated. Characteristics, job possibilities, recruiting statistics, unavoidable leaves, turnover, training, development, and so on

2.4.13 Cisco's HR Advanced Analytics Group

Cisco is an international networking and security solutions company with operations in over 22 nations and around 71,0000 people. Cisco's HR group performs staff morale, retention, and productivity surveys at numerous stages daily. The yearly Pulse Survey gets roughly 50 thousand responses and is extra quantitative, and the Senior Technical Expertise Survey collects qualitative data for pinnacle performers and senior profiles and collects qualitative data. The crew aimed to create a model to decide the traits of excessive-cost personnel in an enterprise, how unique management patterns affect these personnel's satisfaction tiers, and how to use this statistic to retain and put together employees for future roles.

For the evaluation, they hired the IBM SPSS Modeler software program. The crew trained to use an SPSS modeler for data mining and textual content analytics using IBM

accomplice Aviana. Cluster analysis and textual content sentiment evaluation were hired using the team and Aviana's representative. ((Sujeet N. Mishra, 2016))¹((Dey, 2015)²

2.4.14 Starbucks Reinforcement Learning Technology

It is a sort of deep learning where another system learns to conclude complicated, unexpected contexts and focuses on external feedback to give consumers a more customized experience using the Starbucks mobile app. It also established a website entitled "My Starbucks Idea." Salesforce hosts the website. Customers may express their ideas on the website, and the firm receives input from customers to determine where they are outperforming and where they can improve.

2.4.15 Adobe's Personalized HRM

Many HR services, screening job applications, generating employment records, and processing payroll, require repetitive, regular labor. Such mechanical HRM duties are amenable to outsourcing, offshore, and automation. Because of the recent tremendous rise in HR-related technology and software systems, analytical HR functions such as reward policy analysis and HR planning are becoming possibilities for automation.

¹ (Sujeet N. Mishra, 2016))

² (Dey, 2015)²

Although HR analyses are frequently required to conduct primarily analytical HR duties, the effective fulfillment of analytical HR tasks relies on sophisticated HR analytics and AI. One sort of personalized HRM uses AI-powered recommendation engines and machine learning to give employees personalized HRM guidance on training, remuneration, and career development.

2.4.16 Samsung's OJT Strategy

A structured OJT approach facilitates a revolutionary training paradigm known as 'training on-the-job or 'prescriptive training,' in which training sessions schedule when and if needed rather than before the actual performance. It is feasible to propose 'what should be done' to the worker based on context-specific data obtained from the field by integrating predictive/prescriptive approaches, knowledge management, representation techniques, and decision support methodologies. DT data and models are used to automatically develop digital training environments that properly recreate the real operational context that workers would confront. A structured OJT technique that represents implicit procedural knowledge using Evolutionary Fuzzy Cognitive Maps (E-FCM) has been created to maximize training efficacy.

2.4.17 Godrej centralizes HR processes to serve its employees better

HR business partners to supply solutions, HR COE expertise to develop product processes, and any other interventions to deal with day-to-day issues in an organization..

As a result, centralizing the procedures became critical for a few fundamental reasons. "The first is that it consumes a significant amount of bandwidth from HR business partners and COEs because while these processes are important, they do not necessitate high-level expertise." Second, because it has numerous imprints in the exact location, it may not be the same quality as the other.

That is the type of experience we are looking forward to. Third, there is the apparent expense. The concept becomes more scalable as centralization and technology increase. Finally, having a typical data center makes analytics easier to drive (Bhattacharjee, 2021)¹.

2.3.18 McKinsey "Machine Learning Strategy"

McKinsey is a multinational consulting transnational consulting company, and their adventure into predictive analytics analysis of destiny started once they had been accomplishing human beings' analytics. Look at Fort considered one of their customers and have been so thrilled with the consequences that they determined to use it internally. To accumulate statistics for the algorithms, McKinsey held several workshops and interviews, thinking about elements like remuneration, performance critiques, patron remarks, employee engagement facts, training details, and mentoring programs. They

¹ (Bhattacharjee, 2021))

created an in-residence Predictive – Retention set of rules for the evaluation. (Quarterly, 2015)¹

2.5 HOW WORKER ATTRITION IS, IN THE LONG RUN, IMPACTING THE EMPLOYER

2.5.1 Influences the personnel's job security and employee contentment

As per Storey (2016), a differentiation strategy primarily influences the personnel's job security and employee contentment (Asif, 2022)². Several considerations are interwoven since career progression is a motivator for employees. (Khera S. N., 2018)³. The IT industry's dropout rate or staffing shortages should never be a nightmare because of terrible earnings, constrained career development opportunities, and different vital concerns. Organizational culture (Raina, 2016), employment marketing, age and culture, job placement, and substitute careers are a number of those aspects ((Kanwar, 2012)⁴. however, due to the growing boom of an era in India, IT professionals are on an

¹ (Quarterly, 2015)

² (Asif, 2022)

³ (Khera S. N., 2018)

⁴ (Kanwar, 2012)

excessive call, even though fewer onsite chances inspire individuals to move jobs. Employee turnover, consistent with (Margarita, 2016)¹, impacts an enterprise's profitability by increasing indirect manufacturing costs. That is because the IT enterprise offers an expansion of activity-related schooling to personnel. However, if they give up, their rate of return suffers notably as their resources are wasted.

2.5.2 Employee Turnover Impact

Employee turnover (Pratama, 2022)², according (DHILLON, 2016)³, has a significant effect on customer satisfaction for the reason that exceptional services suffer. Moreover, customer lawsuits escalate if the attrition rate maintains excessive and the organization's productivity and profitability go through. Moreover, the enterprise might not hold its competitive advantage within the industry. As a result, employee retention is essential to the IT sector in the direction of long-term growth and success in India.

¹ (Margarita, 2016))

² (Pratama, 2022)

³ (DHILLON, 2016))

The administrative center territory furnishes an ultimatum and prospect that plays an active part; thus, professional Destinations and development therapies are visible in the inspiration linked appreciably with sky-scraping phases of Retention (Singh e. a., 2012)¹. Tremendous and as per the data collected and analyzed, quite apart from the adjustments implemented by the know-how technology, people are persuaded alongside intramural elements like subculture, pay, overall performance, and well-being. To be 'hilarious,' IT professionals must put in much effort. Every IT firm needs to promote itself as a program that provides a work/life balance (Seymour, 2022)² and amusement in strategies to attract and maintain quality employees. (Nayak, 2017)³

The position of the Human Resources Depts within intramural the topic of promotional strategy discussed in order employees are preoccupied with being concerned in search of or even nurturing something trademark, understanding It is indeed enormous and comprises the characteristics of individuals functioning beliefs and actions. (Goessling, 2017)⁴. Additionally, they want to exchange their HR strategy so that perhaps

¹ (Singh e. a., 2012)

² (Seymour, 2022)

³ (Nayak, 2017)

⁴ (Goessling, 2017)

the three different occupational periods are taken into consideration. As previously stated, boomers have exceptional stimulating reasons and movement needs, and they have been lured to companies that offer workplace flexibility, entertaining environments, assignment diversification opportunity, career progression, and research prospects. (Gaye, 2015)¹.

2.5.3 Personnel Wornout and its Impact

Personnel are worn-out, and plenty of them are grieving. They need a renewed and revised sensibility of the reason for their work. They fancy social and interpersonal connections with their colleagues and administrator (To, 2022)². They need to encounter an awareness of shared congruence. Persuaded, they ought to pay, convenience, and perks. However, more significant than that, they need to sense value using their organizations and managers. They need significant—even though not always in-man or woman—interactions, no longer simply transactions s (Smet, 2021)³

¹ (Gaye, 2015)

² (To, 2022).

³ (Smet, 2021)

2.5.4 Reduces Work Satisfaction

Pay and fringe benefits (Zanabazar, 2022)¹ are sizeable determinants that affect workplace fulfillment. The survey's results indicate how they reduce work satisfaction since the typical level among these predictors is lower than the usual step of standard job contentment. Employment happiness is generally elevated via various features, which include guidance, co-workers, and the demands of the job and discussion; which of them has a typical level of excitement higher than 4.00? As a result, an upward pattern toward growing pay levels is unquestionably beneficial for increasing job satisfaction. (Singh P. a., 2016)²

The authors made a sturdy spike at the thrust of Job contentment, employer involvement, continuous improvement, disruptions, willingness to continue, plus the authority of the commitment to remain owing to the authentication they gathered were all factors in their decision to stay. The control should assess these typical behaviors, activities, instances, and forecast updates years so the control gives correct and applicable data to guide the retention procedure. Fulfillment may be seen in massive businesses where the pinnacle control crew seems encouraging systematically as a concern, retention

¹ (Zanabazar, 2022)

² (Singh P. a., 2016)

tactics, and the development of effective Human resource management practices (Lee, 2018)¹.

Onboarding apps, acquiring to recognize and proposals including (Ranjan, 2022)², are vital to sustaining talented leaders, per the article "talent management method of employee engagement in Indian ITES Personnel: Key to Retention." (Bhatnagar, 2007)³

Recurring verbal exchanges ought to be hooked up with the presence of company leadership. Thriving leaders is a prerequisite for successful leadership achievement (Berry, 2008)⁴. Various factors, including quality and regulations, are influenced by career enhancement, job control, readability of verbal exchange, flexibility in operating preparations, and Work engagement. (Berry, 2008)⁵.

¹ (Lee, 2018)

² (Ranjan, 2022),

³ (Bhatnagar, 2007)

⁴ (Berry, 2008)

⁵ (Berry, 2008)

2.6 SUMMARY

The Great Shrinkage could become the Great Allure if companies consciously attempt to comprehend why people are leaving and respond appropriately to retain them. By grasping this once-in-a-lifetime opportunity, companies could gain a competitive edge to acquire, train, and maintain the people they need to build a robust post-pandemic organization.

Executives who struggle to implement their employees feel appreciated can drive them out of their firms, not just whether those who have a new job lined up. It would help if we sorely had leaders who could excite and empower their teams while leading with humanity.

It is true in hybrid environments, wherever new leadership abilities demand. Management types would need to invest in training and capability enhancement.

2.7 CONCLUSIONS

DDDM-HR Analytics has benefits throughout proactive, reactive, predictive, and strategic decision-making. The research strongly implies that 'Analytics' is incorporated into the application of human resource management in achieving a shot on target on utilization of resources. Daily practice comparing information collected by HR professionals from other departments to what the data analytics team needs for the future. The predictive parameters must be proportioned and reviewed through Human aid and

different departments for her internal assessment and execution-based decision-making. The business enterprise's Human capital supply should maximize with the best admissible productiveness via analytically assessing the modern-day and ability talent pool. To estimate the Behavioral capability set wanted in upcoming human resources for us to characteristic as a group within the commercial enterprise, Behavioral and social forecasts must use. To introduce HR and Analytics features, it is miles inevitable to layout and beautifies the same old practices.

CHAPTER III

METHODOLOGY

3.1 OVERVIEW OF THE RESEARCH PROBLEM

Employee attrition is the voluntary or involuntary reduction of employees in an organization for various reasons, such as retirement, resignation, and termination. Employee attrition is a severe problem for many organizations, as it leads to various costs and risks, such as reduced productivity, lower quality of work, loss of knowledge and skills, increased recruitment and training expenses, decreased morale and commitment among the remaining employees, and disruption of teamwork and collaboration. Moreover, employee attrition has become even more prevalent and problematic for many organizations in the current pandemic and economic uncertainty scenario.

The main objective of this research is to study the problem of employee attrition and predict its occurrence based on the behavioral patterns of employees. The research explores the factors influencing employees' decisions to stay or leave their jobs, such as monetary terms, work-related causes, pandemic effects, bossism, social attributes, and personal attributes. The research aims to identify the primary reasons for employee attrition and suggest appropriate retention strategies to control human capital through data-driven people analytics.

Data-driven people analytics uses data and analytical techniques to understand and improve various aspects of people management, such as hiring, performance, engagement, and retention, diversity. Data-driven people analytics can help HR managers to make informed and evidence-based decisions that can enhance organizational effectiveness and employee well-being. By using data-driven people analytics, HR managers can identify the patterns and trends of employee attrition and its impact on organizational outcomes, segment the employees into different groups based on their attrition risk and retention potential, understand the drivers and barriers of employee retention and satisfaction, develop and implement customized and targeted interventions to reduce employee attrition and increase employee loyalty, monitor and evaluate the effectiveness of retention strategies and adjust them as needed, and communicate and justify the value and benefits of retention strategies to the top management and other stakeholders.

Questionnaire survey methodology the research will use a quantitative approach to collect and analyze data from a sample of employees from different organizations. The research will use various statistical and machine-learning techniques to test the hypotheses and answer the research questions. The research will contribute to the existing literature on employee attrition and retention by providing a comprehensive and data-driven analysis of the problem. The research will also provide practical implications and recommendations for HR managers and policymakers on reducing employee attrition and enhancing employee retention using data-driven people analytics.

Employee attrition analytics uses data and statistical methods to understand and predict why employees leave an organization, what might have prevented them from leaving, and how to reduce unwanted attrition.

Some of the benefits of employee attrition analytics are:

- It helps to identify the factors influencing employee attrition, such as job satisfaction, work-life balance, compensation, and career growth.
- It helps to measure the impact of employee attrition on organizational outcomes, such as customer satisfaction, innovation, and profitability.
- It helps to design and evaluate the interventions that can improve employee retention, such as recognition programs, training opportunities, and flexible work arrangements.
- It helps to forecast future attrition trends and risks and plan accordingly for talent acquisition and development.

Some of the standard methods of employee attrition analytics are:

- Logistic regression and decision trees for explaining employee attrition using data.
 - Support vector machine, random forest, k-nearest neighbor, and naive Bayes for predicting employee attrition using data. Surveys and interviews for understanding employee satisfaction, engagement, motivation, and loyalty.
 - Attrition analysis for reporting the details and reasons employees leave the company.
-

3.2 OPERATIONALIZATION OF THEORETICAL CONSTRUCTS

Operationalization of theoretical constructs means defining and measuring the abstract concepts that are related to the phenomenon of employee attrition. Employee attrition is the voluntary or involuntary reduction of employees in an organization for various reasons, such as retirement, resignation, and termination.

Some examples of theoretical constructs that could be relevant for studying employee attrition are:

- **Turnover intention:** The degree to which an employee plans to leave their job shortly.
 - **Employee engagement:** The extent to which an employee gets involved in the job and the organization cognitively, emotionally, and behaviorally.
 - **Job satisfaction:** The degree to which an employee feels positive or negative about various aspects of their job, such as pay, work environment, and supervision.
 - **Organizational commitment:** The degree to which employees identify with and feel loyal to their organization and its goals.
-

Among these, we are targeted for employee turnover intention or employee attrition.

To operationalize these constructs, one must choose appropriate variables and indicators that capture their meaning and variation. Variables are observable and measurable representations of the constructs, while indicators are the specific items or questions used to measure the variables. For example:

- Turnover intention is operationalized as a variable that is measured by a single indicator that asks the employees to rate their likelihood of leaving their current job in the next year on a scale from 1 (very unlikely) to 5 (very likely).
 - Employee engagement can be operationalized as a variable consisting of three dimensions: cognitive, emotional, and behavioral. Each dimension can be measured by a set of indicators that ask the employees to rate their agreement with statements such as "I am enthusiastic about my job," "I feel a strong sense of belonging to my organization," or "I am willing to go beyond my formal job responsibilities."
 - Job satisfaction can be operationalized as a variable consisting of several facets: pay satisfaction, work satisfaction, and supervision satisfaction. Each facet can be measured by a set of indicators that ask the employees to rate their satisfaction with statements such as "I am satisfied with my pay level," "I am satisfied with the work I do," or "I am satisfied with my supervisor."
-

- Organizational commitment can be operationalized as a variable that consists of three components: affective commitment, continuance commitment, and normative commitment. Each component can be measured by a set of indicators that ask the employees to rate their agreement with statements such as "I feel emotionally attached to this organization," "I stay with this organization because I have no other alternatives," or "I stay with this organization because I feel obligated to do so."

Operationalization of theoretical constructs is essential for ensuring the validity and reliability of the research findings. Validity refers to the extent to which the variables and indicators accurately measure what they are intended to measure, while reliability refers to the extent to which the variables and indicators produce consistent and stable results. Choosing appropriate variables and indicators for each construct can increase the chances of obtaining valid and reliable data on employee attrition.

3.3 RESEARCH PURPOSE AND QUESTIONS

3.3.1 Research Purpose

Retaining good employees is vital for every organization, public or commercial. According to the literature and best practices, employers treat their staff as valuable contributors. Organizations train their managers, give competitive compensation schemes, and expand their perks to ensure employee loyalty. Despite these efforts, many organizations face a labor shortage and high turnover rates. The success of every

organization is primarily dependent on its workforce or workers. Employees are regarded as the organization's backbone. At the same time, employees should be happy with what the business has invested or will invest in their professional development. Atanu Adhikari addressed only particular concerns connected to the environmental study of difficulties, growth, and opportunities, the problem of attrition, the HRM system, job stress issues, employee happiness, individual performance, and so on in his Factors Affecting Employee Attrition. This study is being conducted to discover some significant dissatisfaction people confront in the organization and why they prefer to change employment.

Furthermore, this could not have occurred using the same tactics. Even the strategies must be altered. As a result, this research can aid in understanding the attitudes and behaviors of the organization's personnel. It would aid in understanding why an employee wants to quit the organization and which variables contribute to his or her decision. Strategies should be devised in such a way that they foster and preserve long-term relationships with employees. The company should provide employment that is difficult, fascinating, and fulfilling.

The purpose of this research is to study the problem of employee attrition and predict its occurrence based on the behavioral patterns of employees. The research aims

to identify the primary reasons for employee attrition and suggest appropriate retention strategies to control human capital through data-driven people analytics.

3.3.2 The Research Questions

- Can We Predict Employee Attrition Through Employee behavioral patterns Advancement Using BI Tools?
 - What are the retention strategies playing a pivotal role in terms of retaining the skilled professional?
 - Finding out the various reasons for employee churn
 - Identify the impulsive factors which determine employee attrition
 - Elevate Significant after-effects due to employee attrition
 - Analyze employees satisfied with their pay for the job role
 - Assess employees who feel overworked and micromanaged.
 - Evaluate on employee receives training, new opportunities, and growth prospects within the organization.
 - Identify whether the company work culture aligns with the employee's values and does the boss give room to grow.
 - Discuss with employees on their expectations in the post-pandemic era from their employer.
 - Evaluate the organization's offers to the resigned employees if he/she consents to continue their services.
-

- Identify the correlation between the considered data attributes
- Dept, age, pay scale, job satisfaction, and training attributes impact employee churn.

3.4 RESEARCH DESIGN

Conducting mixed-methods research that combines qualitative and quantitative data. Here is a possible research design for our research:

- **Research question:** How can data-driven decision-making (DDD) help HR managers reduce employee attrition?
- **Research approach:** Mixed methods, using a sequential explanatory design. We will first collect and analyze quantitative data and then use the results to guide the collection and analysis of qualitative data.

3.4.1 Quantitative phase

- **Sampling method:** Random sampling from the KNIME employee attrition dataset, with a sample size of 1470 and 32 attributes.
 - **Data collection method:** Secondary data analysis of the KNIME dataset is used.
 - **Data analysis method:** Comparative analysis of ML algorithms (random forest, SVM, logistic regression, tree ensemble, nearest neighbor) is used to predict employee attrition and identify the most critical factors.
-

3.4.2 Qualitative phase

- **Sampling method:** Purposive sampling from the survey responses of 108 employees who participated in the qualitative phase, selecting those with high or low attrition risk according to the ML predictions.
- **Data collection method:** Semi-structured interviews with the selected employees, using open-ended questions to explore their experiences, perceptions, and motivations related to DDD and employee retention.
- **Data analysis method:** Thematic analysis of the interview transcripts, using KNIME software to code and categorize the data into themes and subthemes.

3.4.3 Decision Tree Analysis

The study used a **Decision Tree Algorithm** to predict and set the rules about employee attrition based on various features such as age, education, job role, salary, and other attributes., using the KNIME employee attrition Dataset. Another study used a **Deep Data-Driven Approach** based on a mixed method to construct a relevant employee attrition model using **Qualitative and Quantitative Data**.

3.5 POPULATION AND SAMPLE

3.5.1 Population

As of the end of March 2020, India had 4.36 million IT personnel, estimated to the National Association of Software and Services Companies (NASSCOM). All of

India's IT professionals make up the study's target group. The following standards are used to define the population:

- The employee works in the IT sector, which includes software development, IT services, business process management, engineering services, Research and Development, and others.
- The employee is based in India, regardless of the location or nationality of the employer.
- The employee is employed full-time or part-time, excluding freelancers or contractors.

3.5.2 Sample

This study's sample comprises a subgroup of IT personnel from a giant multinational corporation with operations in India. The company has agreed to provide access to its employee data for this research. The sample is selected using a stratified random sampling method, which involves dividing the population into homogeneous groups (strata) based on relevant characteristics and then randomly selecting a proportionate number of individuals from each group. The strata for this study are based on the following characteristics:

- The employee's role includes software engineer, software tester, software analyst, and project manager.
 - The employee's experience level includes entry-level, mid-level, and senior-level.
 - The worker's gender might be male or female to consider.
-

Depending on our sampling method and research design, there are different formulas and methods for calculating the sample size. For example, if we are using a simple random sampling method and a quantitative research design, we can use the following formula for calculating the sample size:

$$n = \frac{z^2 p(1 - p)}{e^2}$$

Where:

- n is the sample size
- z is the z-score corresponding to our confidence degree (1.96 for a 95% confidence level).
- p is the estimated proportion of success in our population (for example, 0.5 for maximum variability)
- e is the margin of error (for example, 0.05 for a 5% margin of error)

Using this formula, we can calculate our sample size by plugging in our z, p, and e values. For example, if we want to achieve a 95% confidence level and a 5% margin of error with maximum variability, our sample size would be:

$$n = \frac{1.96^2 \times 0.5 \times (1 - 0.5)}{0.05^2} = 384.16$$

can round up this number to get the final sample size of 385.

Online calculators and software tools can help us calculate our sample size based on our inputs and assumptions.

Conclusion

The population and sample section has defined and described the target population and the sample for this study. The population consists of all IT employees in India, while the sample consists of a stratified random sample of IT employees from different organizations. The sampling method and sample size of 108 through the survey method as primary data and for a quantitative sample size of 1470 are justified and explained based on statistical calculations and practical considerations. The population and sample are relevant and representative of answering this study's research question and objectives.

3.6 PARTICIPANT SELECTION

There are two kinds of sampling procedures (confidence level): probability sampling and non-probability sampling. Probability sampling involves randomly selecting participants from the population, ensuring everyone has an equal chance of being selected. Non-probability sampling involves randomly selecting participants based on convenience, availability, or other criteria, without ensuring equal population representation.

The choice of sampling method depends on various factors, such as:

- The research design and methodology
- The research question and objectives
- The population size and characteristics
- The availability and accessibility of data
- The time and budget constraints
- The desired level of generalizability and validity

Some advantages and disadvantages of different sampling methods are:

- **Probability sampling** allows us to draw statistical conclusions and generalizations about the population based on the sample data. It reduces the risk of bias and sampling error. However, it requires a complete and accurate list of the population (sampling frame), which may not be available or feasible. It also requires more time and resources to implement and may result in low response rates or non-responses.
 - **Non-probability** sampling allows us to collect data quickly and easily from a convenient or accessible sample. It does not need the use of a sample frame or random selection. It may be suitable for exploratory or qualitative research that does not aim to generalize to the population. However, it limits the validity and reliability of the results and may introduce bias and sampling error. It does not allow you to make statistical inferences or generalizations about the population based on the sample data.
-

Some examples of probability sampling methods are:

- **Simple random sampling:** Every member of the population has an equal probability of being chosen for the sample. It can be done using a random number generator or a lottery system.
- **Systematic sampling:** Every n th individual in the population is selected for the sample, where n is a fixed interval determined by dividing the population by the desired sample size. It can be done using a list of the population and a random starting point.
- **Stratified sampling:** involves dividing the population into homogenous groups (strata) based on relevant criteria (such as gender, age, geography, and so on) and then drawing a simple random sample from each group proportionately or equally.
- **Cluster sampling:** The population is split into heterogeneous groups (clusters) based on geographical or administrative boundaries (such as regions, districts, schools, and so on), and a simple random sample of clusters is drawn. The sample includes all individuals in the specified clusters, or a simple random sample is generated from each cluster.

Some examples of non-probability sampling methods are:

- **Convenience sampling:** The sample consists of individuals who are readily available or accessible to the researcher (such as students in a classroom, customers in a store, and online respondents.).
-

- **Purposive sampling:** The sample consists of selected individuals based on their relevance or suitability for the research question and objectives (such as experts in a field, key informants, and typical or extreme cases.).
- **Quota sampling:** The sample consists of individuals selected based on predefined quotas or proportions that reflect the characteristics of the population (such as gender, age, location.). The quotas are filled by convenience or purposive sampling.
- **Snowball sampling:** The sample consists of individuals identified by referrals from existing participants who share similar characteristics or experiences (such as social network members, hard-to-reach populations.).

Our research used stratified, convenience, and quota sampling methods into consideration.

3.7 INSTRUMENTATION

Exploratory data analysis, evaluation of various models, and visualization of the hypothesis purpose we have used three different instruments

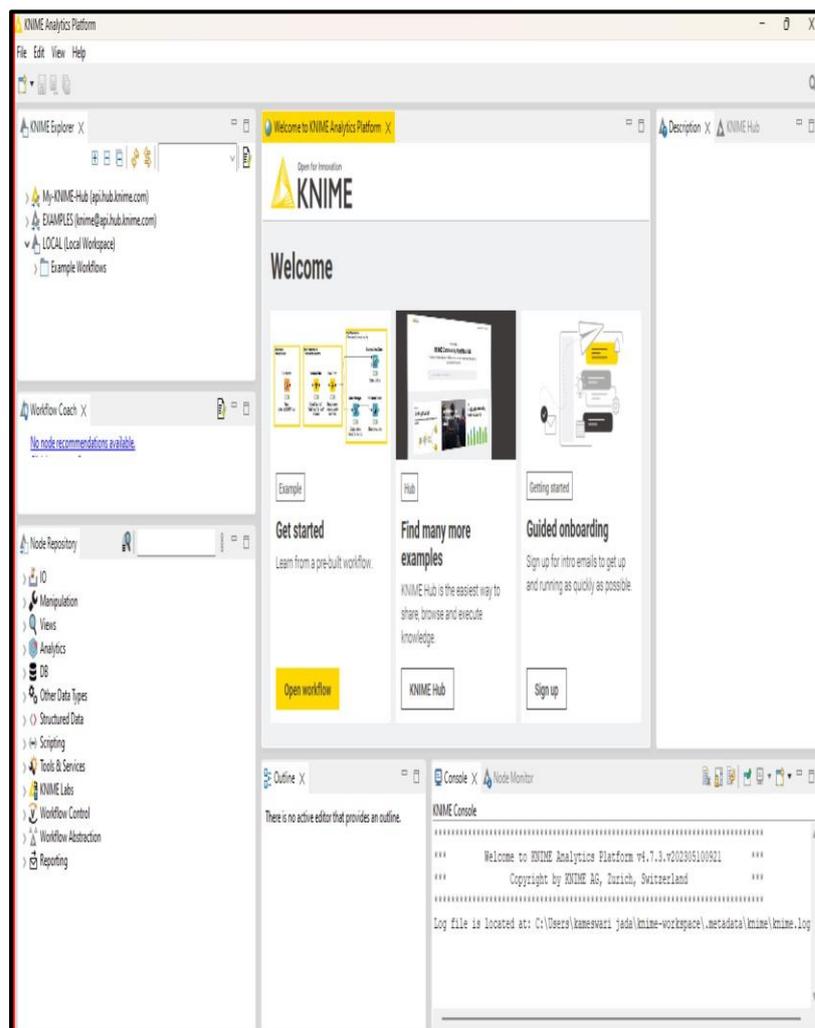
1. Knime analytical tool
 2. Jupyter notebook
 3. Advanced Excel for plotting
 4. MS Power BI
 5. Tableau
-

3.7.1 KNIME Analytics Platform:

KNIME Analytics Platform is open-source software that allows users to access, blend, analyze, and visualize data without coding¹. It has a low-code, no-code interface that offers an accessible introduction for beginners and an advanced data science set of tools for experienced users.

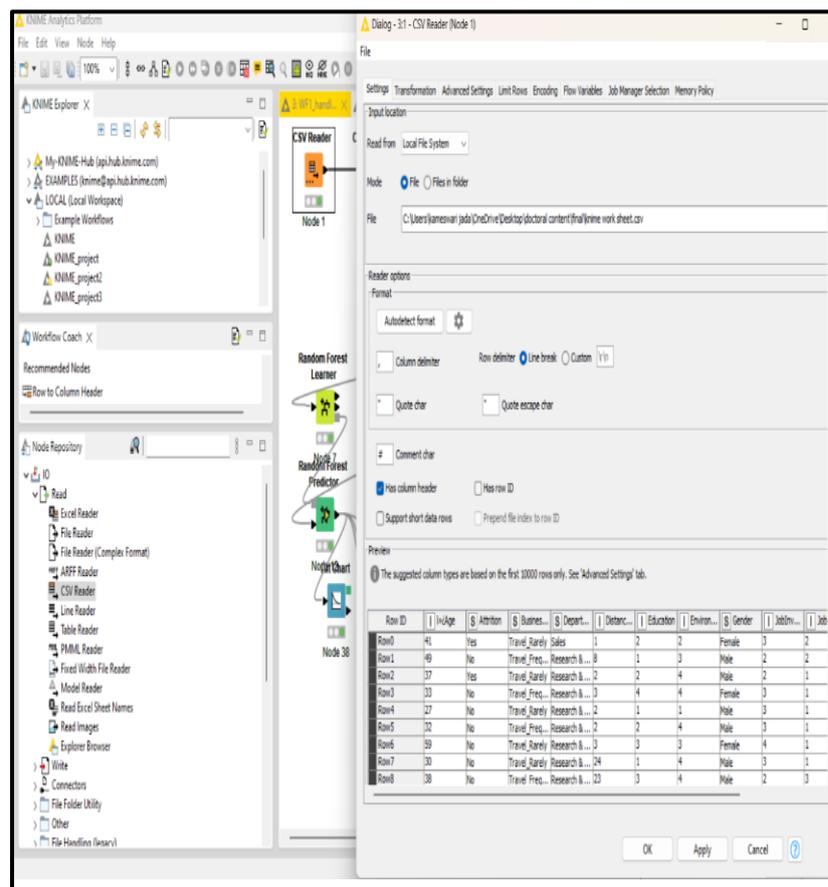
Figure 16 KNIME Analytics Platform Appearance





KNIME Analytics Platform lets create visual workflows for data analytics by joining nodes together via an intuitive, drag-and-drop interface. Nodes designed to perform discrete actions on data, such as reading, writing, transforming, modeling, or visualizing. We can use thousands of nodes from KNIME or other popular machine-learning libraries, such as TensorFlow, Keras, H2O, and more.

Figure 17 Example of KNIME work flow and CSV file Reading



Here is an example of a KNIME workflow that reads data from a CSV file and displays the file in a knime workbook:

KNIME Analytics Platform also allows us to blend data from any source, such as text formats (CSV, PDF, XLS, JSON, & XML.), unstructured data (images, text, networks, sound, and molecules), or databases and data warehouses (SQL Server, Postgres, MySQL, Snowflake, Redshift, and BigQuery). We can also shape our data by

deriving statistics, applying statistical tests, aggregating, sorting, filtering, joining, cleaning, detecting outliers and anomalies, extracting and selecting features, and manipulating text and numerical data.

Moreover, the KNIME Analytics Platform enables us to leverage machine learning and AI techniques for classification, regression, dimension reduction, clustering, deep learning, tree-based methods, logistic regression, and more. We can also validate our models by applying performance metrics such as accuracy, R², AUC, and ROC. Additionally, we can deploy our workflows as web applications or services that other users or systems can consume.

Many data analysis tools are available in the market, such as R, Python, Tableau, Alteryx, RapidMiner, IBM SPSS Modeler, and more. Each tool has strengths and weaknesses, depending on the use case and the user's preference.

Some of the standard criteria for comparing Data Analysis tools are:

- **Open Source vs. Proprietary:** Some tools are free and open source, such as KNIME, R, and Python, while others are proprietary and require a license fee, such as Alteryx, Tableau, and IBM SPSS Modeler. Open-source tools offer more flexibility and customization, while proprietary tools offer more support and security.
 - **Programming vs. Visual Interface:** Some tools require coding skills, such as R and Python, while others provide a visual interface for creating data workflows, such as
-

KNIME, Alteryx, and Tableau. Programming tools offer more control and complexity, while visual tools offer simplicity and ease of use.

- **Data Manipulation vs. Visualization:** Some tools are more focused on data manipulation and analysis, such as KNIME, R, and Python, while others are more focused on data visualization and storytelling, such as Tableau. Data manipulation tools offer more functionality and versatility, while data visualization tools offer more interactivity and appeal.

Based on these criteria, here is a brief comparison of KNIME with some of the popular data analysis tools:

- **KNIME vs. R:** Both are open source and can be used to manipulate, visualize and analyze data. However, KNIME provides a visual interface for creating data workflows, making it easy for users to import, manipulate, visualize, and analyze data. R is a programming language that requires coding skills and is known for its powerful statistical capabilities.
 - **KNIME vs. Python:** Both are open source and can be used to manipulate, visualize and analyze data. However, KNIME provides a visual interface for creating data workflows, making it easy for users to import, manipulate, visualize, and analyze data. Python is a general-purpose programming language that requires coding skills and is known for its simplicity and machine-learning libraries.
 - **KNIME vs. Tableau:** Both provide a visual interface for creating data workflows. However, KNIME focuses more on data manipulation and analysis, while Tableau
-

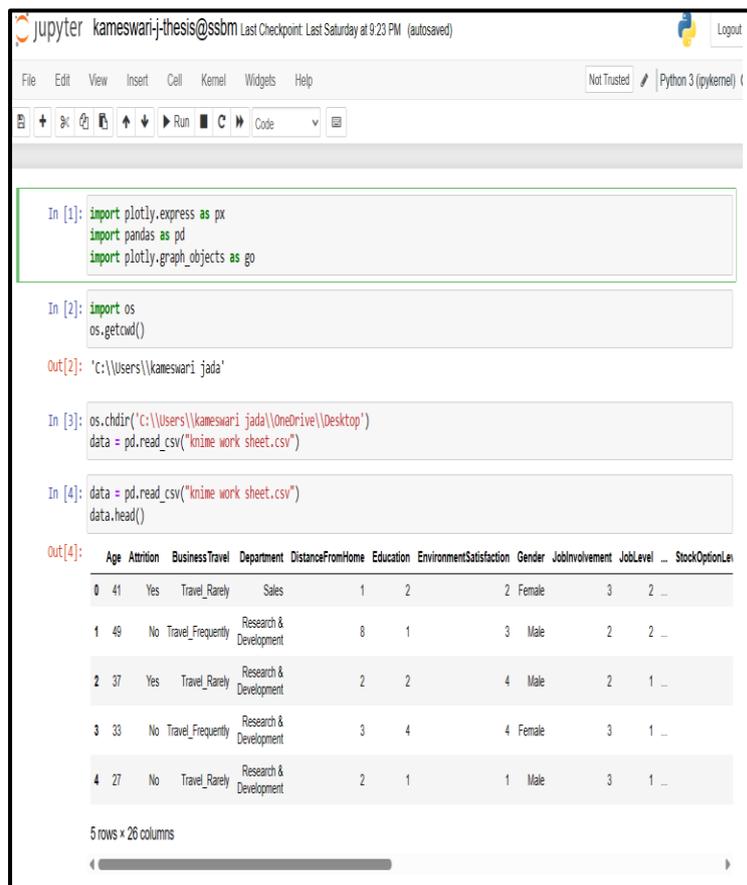
focuses more on data visualization and storytelling. KNIME offers many built-in nodes for data manipulation, visualization, and analysis. Tableau offers a wide range of built-in charts and dashboards for creating interactive and visually appealing data visualizations.

- **KNIME vs. Alteryx:** Both provide a visual interface for creating data workflows. However, KNIME is open source, while Alteryx is proprietary. KNIME offers more customization and reliability, while Alteryx offers more simplicity and user-friendliness. KNIME has many built-in nodes for data manipulation, visualization, and analysis. Alteryx has functions where users can drag and drop to pick a data type and connect to a database.
 - **KNIME vs. RapidMiner:** Both provide a visual interface for creating data workflows. However, KNIME is open source, while RapidMiner is proprietary. KNIME offers more flexibility and integration, while RapidMiner offers more automation and optimization. KNIME has many built-in nodes for data manipulation, visualization, and analysis. RapidMiner has features that allow users to automate data preparation, model building, and deployment.
 - **KNIME vs. IBM SPSS Modeler:** Both provide a visual interface for creating data workflows. However, KNIME is open source, while IBM SPSS Modeler is proprietary. KNIME offers more versatility and functionality, while IBM SPSS Modeler offers more support and security. KNIME has many built-in nodes for data manipulation, visualization, and analysis. IBM SPSS Modeler has features allowing users to apply advanced statistical techniques and predictive analytics.
-

3.7.2 Jupyter Notebook

A Jupyter Notebook is a free and open-source web tool that allows data scientists to create and share documents with live code, equations, and other multimedia elements. It is a well-known interactive computing and data analysis tool used mainly in Python.

Figure 18 Jupyter Notebook appearance and CSV File Reading



The screenshot shows a Jupyter Notebook interface with the following code and output:

```
In [1]: import plotly.express as px
import pandas as pd
import plotly.graph_objects as go
```

```
In [2]: import os
os.getcwd()
```

```
Out[2]: 'C:\Users\kameswari.jada'
```

```
In [3]: os.chdir('C:\Users\kameswari.jada\OneDrive\Desktop')
data = pd.read_csv("kime work sheet.csv")
```

```
In [4]: data = pd.read_csv("kime work sheet.csv")
data.head()
```

```
Out[4]:
```

	Age	Attrition	BusinessTravel	Department	DistanceFromHome	Education	EnvironmentSatisfaction	Gender	JobInvolvement	JobLevel	StockOptionLe
0	41	Yes	Travel_Rarely	Sales	1	2	2	Female	3	2	...
1	49	No	Travel_Frequently	Research & Development	8	1	3	Male	2	2	...
2	37	Yes	Travel_Rarely	Research & Development	2	2	4	Male	2	1	...
3	33	No	Travel_Frequently	Research & Development	3	4	4	Female	3	1	...
4	27	No	Travel_Rarely	Research & Development	2	1	1	Male	3	1	...

5 rows x 26 columns

A Jupyter Notebook consists of cells containing code or markdown text. Code cells can be executed and display the output below the cell. Markdown cells can be used to write formatted text, equations, images, and more. A Jupyter Notebook can display interactive widgets like sliders, buttons, and graphs.

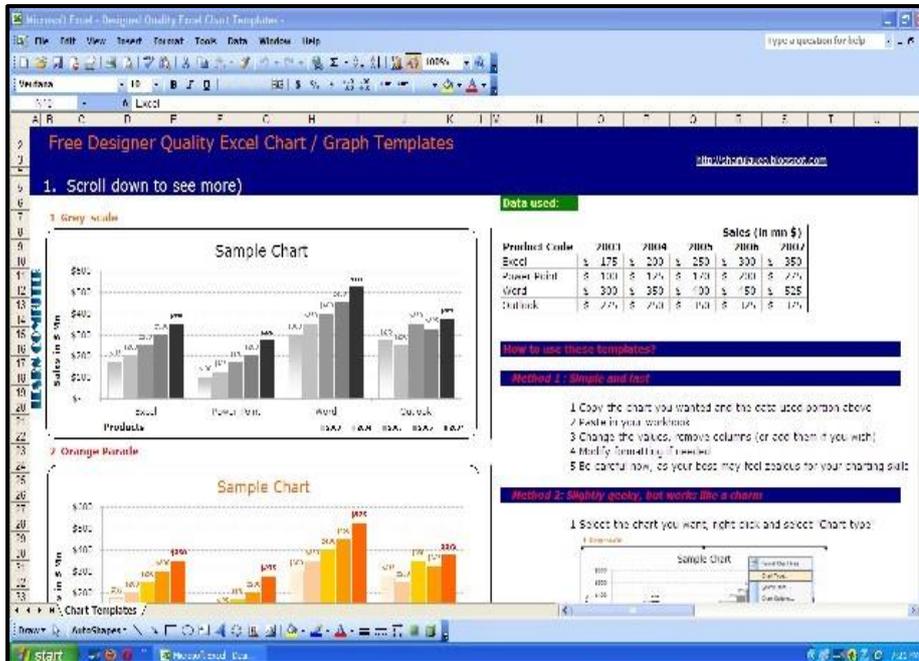
To use a Jupyter Notebook, install it on your computer or use an online service. To open a Jupyter Notebook, launch the Jupyter server from our terminal or command prompt and then access the notebook interface from our web browser². We can also use a cloud platform like Databricks that integrates with Jupyter Notebooks.

A Jupyter Notebook is a powerful data exploration, visualization, and communication tool. We can use it to write code, run experiments, document our findings, and share our results with others. We can also learn new skills like programming languages, data science techniques, and machine learning algorithms.

3.7.3 Microsoft Excel:

Microsoft Excel is a spreadsheet software program that allows users to collect, process, and display numerical data¹. It is a powerful data visualization and analysis tool that can be used for various purposes, such as budgeting, accounting, forecasting, reporting, and more.

Figure 19 Microsoft Excel Appearance during Data Analysis



Microsoft Excel uses a grid of cells arranged in numbered rows and letter-designated columns to organize data input. Users can enter data, formulas, functions, charts, and other elements into the cells to perform calculations and create visualizations. Users can also use features such as pivot tables, slicers, and filters to manipulate and explore data.

Microsoft Excel also supports a macro-programming language called Visual Basic for Applications (VBA), which allows users to automate tasks and customize the functionality of Excel. Users can write VBA code in the Visual Basic Editor (VBE) or record macros using the Macro Recorder.

Microsoft Excel is part of the Microsoft 365 application suite, including Word, PowerPoint, OneNote, and Outlook. Users can access Excel on their devices using a web browser or install it on their computers. Users can also use the Microsoft 365 mobile app to access Excel on their smartphones or tablets.

3.7.4 POWER BI

Microsoft Power BI is a data visualization and business intelligence tool that translates data from diverse data sources to generate various business intelligence reports. It enables interactive visualizations via which end users may design their reports and interactive dashboards.

The Power BI tool is a set of apps, data connectors, and software services that take data from many sources, convert it, and generate usable reports. Power BI services are based on SaaS and mobile Power BI applications for various platforms.

Some of the implications of Power BI in visualization are:

- It allows users to quickly and easily explore and analyze data using natural language searches and drag-and-drop functionalities.
 - It enables users to customize and share their visualizations with others, whether online or offline, using Power BI Desktop, Power BI Service, or Power BI Mobile applications.
-

- It can connect to live or imported data and supports various data sources, from Excel files to cloud services to big data platforms.

Figure 20 Microsoft Power BI tool in Data Analysis



- It provides a wide range of visualization forms, including charts, maps, tables, gauges, cards, and more, and the option to generate bespoke visuals in R or Python.
 - It works with Microsoft products, including Excel, SharePoint, Teams, Dynamics 365, Azure, and third-party apps and services.
-

3.7.5 Tableau

Tableau is a powerful and user-friendly data visualization tool that can help HR analysts explore, analyze, and communicate data effectively and engagingly. Tableau can connect to various data sources, such as databases, spreadsheets, files, or web services, and transform the data into interactive dashboards and reports that can be shared and accessed online or offline.

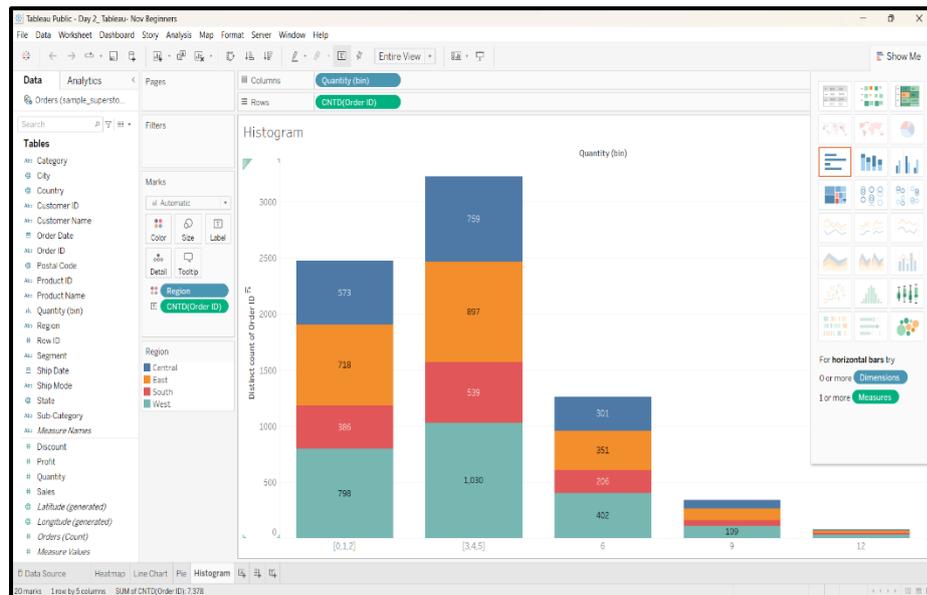


Tableau has many features and benefits that make it a suitable tool for HR analysts, such as:

- It can handle large and complex data sets quickly and easily, allowing HR analysts to perform various data analysis tasks, such as filtering, sorting, grouping, aggregating, calculating, etc., without writing any code.

- It can create various types of data visualizations, such as charts, graphs, maps, and tables, that can reveal patterns, trends, outliers, correlations, and insights from the data. Tableau also supports advanced visual analytics techniques, such as clustering, forecasting, trend, and reference lines, to enhance data analysis and interpretation.
 - It can customize and format the data visualizations according to the preferences and needs of the HR analysts and their audience. Tableau allows HR analysts to choose different colors, shapes, sizes, fonts, labels, legends, and tooltips, to make the data visualizations more appealing and informative.
 - It can create interactive and dynamic dashboards and stories that combine multiple data visualizations and allow the users to interact with the data using filters, parameters, and actions. Tableau also enables HR analysts to add annotations, comments, images, and web pages, to the dashboards and stories to provide more context and explanation.
 - It can publish and share the data visualizations with other users within or outside the organization using Tableau Server or Tableau Online. Tableau also allows HR analysts to embed the data visualizations into other applications or websites using Tableau Public or Tableau Reader. Tableau also supports user collaboration and feedback through subscriptions, alerts, and comments.
-

Tableau has many implications and applications in visualization for HR analysts.

Some of the examples are:

- HR analysts can use Tableau to track and monitor various HR metrics and indicators, such as headcount, turnover rate, attrition rate, hiring rate, retention rate, and diversity rate and compare them across different dimensions, such as time, department, location, gender, and age.
- HR analysts can use Tableau to understand and improve various aspects of employee management, such as recruitment, performance, engagement, satisfaction, and development and identify the drivers and barriers of employee retention and loyalty.
- HR analysts can use Tableau to create and communicate data-driven stories and reports that can inform and influence the HR managers' and leaders' decision-making and strategy. Tableau can help HR analysts to present the data in a clear, concise, and compelling way that can highlight the key findings, insights, and recommendations

3.8 DATA COLLECTION PROCEDURES

Data-driven decision-making on employee attrition and implementing retention measures is an exciting topic.

Data collection procedures for employee attrition may involve the following steps:

- We collect employee data from various sources, such as HR records, surveys, performance reviews, and exit interviews.
-

- We analyze the data using descriptive and inferential statistics, such as turnover rate, turnover cost, and turnover risk.
- We apply machine learning techniques like Random Forest and decision tree algorithms to find patterns and factors influencing employee attrition and create a predictive attrition model.
- Report the findings and recommendations based on the data analysis and the predictive model.

Collecting employee data from various sources is the first step in data collection procedures for employee attrition. It involves gathering relevant information about the employees and their work experiences, such as:

- **HR records:** These may include data on employee demographics, job roles, compensation, benefits, performance reviews, and training.
 - **Surveys:** These may include data on employee engagement, satisfaction, motivation, commitment, and loyalty.
 - **Exit interviews** may include data on why employees leave the organization and their feedback on the work environment, culture, and management.
 - **Other sources:** These may include data from external sources, such as labor market trends, industry benchmarks, and competitor analysis.
-

The purpose of collecting employee data from various sources is to have a comprehensive and accurate picture of the employee population and their turnover patterns. It can help identify the factors influencing employee attrition and the potential interventions to reduce it.

Analyzing the data using descriptive and inferential statistics is the second step in data collection procedures for employee attrition. It involves using mathematical methods to summarize and interpret our collected data. Some examples of descriptive and inferential statistics are:

- **Descriptive statistics:** These are used to describe and organize the data, such as the mean, median, mode, standard deviation, frequency, and distribution.
- **Inferential statistics:** These are used to draw conclusions and make predictions about the population based on the sample data, such as hypothesis testing, confidence intervals, and correlation, regression.

Specific inferential statistics that can be used to analyze employee attrition are:

- **Turnover rate:** This is the percentage of employees who leave the organization in a given period. It can be calculated by dividing the number of employees who left by the average number of employees in that period.
 - **Turnover cost:** This is the amount of money the organization spends on replacing the employees who leave. It can include direct costs (such as recruitment, training, and
-

severance pay.) and indirect costs (such as lost productivity, reduced quality, and lower morale.).

- **Turnover risk** is the probability that an employee will leave the organization shortly. It can be estimated using predictive models that consider factors influencing employee attrition, such as job satisfaction, engagement, and performance.

Analyzing the data using descriptive and inferential statistics is to understand the patterns and trends of employee attrition and identify the key drivers and predictors. It can help formulate hypotheses and test them using statistical methods

3.9 DATA ANALYSIS

A data-driven strategy bases judgments and actions on data analysis rather than intuition or opinion. We want to look at how data-driven decision-making might assist in minimizing staff churn. Some current research has employed various approaches and datasets to address this issue. One study, for example, utilized the IBM dataset and a decision tree algorithm to forecast employee attrition based on factors such as age, education, job type, and income. Another research used a deep data-driven strategy based on a mixed technique to create an effective employee attrition model by merging qualitative and quantitative data.

A deep data-driven strategy is a more sophisticated and complete method for understanding complex problems and developing solutions. Deep learning techniques utilized in this procedure, a subset of machine learning and artificial intelligence, use

artificial neural networks to learn from enormous amounts of data. Deep learning may aid in producing accurate forecasts by extracting temporal and geographical features from spatiotemporal data such as meteorological data. In addition, a deep data-driven strategy can leverage qualitative and quantitative data to build appropriate models that reflect the underlying patterns and correlations. A comprehensive data-driven strategy may assist in overcoming the constraints of traditional methodologies, providing additional insights and value for various applications.

3.9.1 Feature Importance Extraction through Random Classifier Method

For further research on employee attrition impulsive attribute identification, the purpose we made impulsive behavioral patterns divided into three critical, impulsive elements, which referred to as

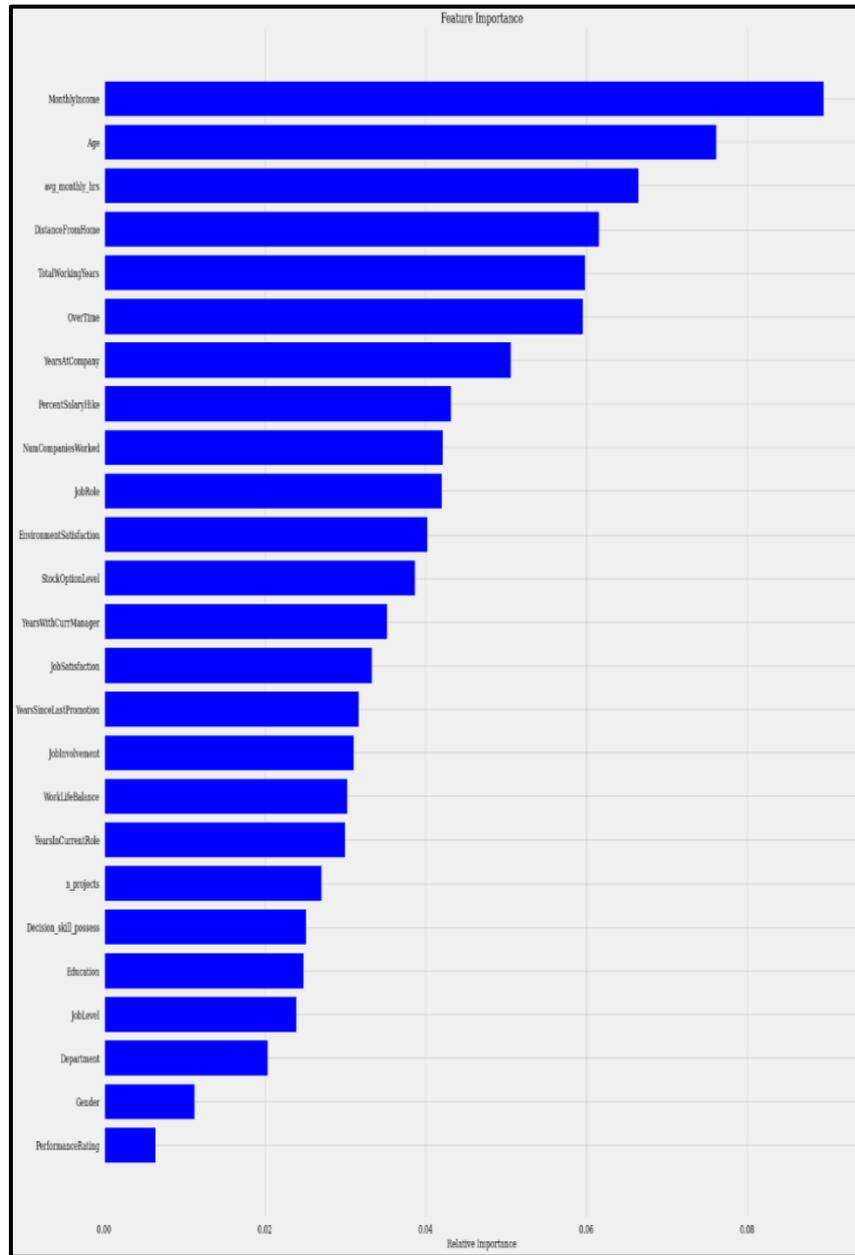
- **Employee Personal Attributes:** These features indicate individual attributes more susceptible to employee attrition. Hence age, business travel, distance from home, education, gender, dept Employee Turnover is the response variable, while others are the control variables.
 - **Employee Work-related Attributes:** Features significant about employee work and organization-based triggering points towards employee churn. So, environment satisfaction, job involvement, job level, relationship satisfaction, average monthly hours,
-

no of projects, decision skill possessed, and work-life balance is taken as the response variable, while are the control variables.

- **Employee Salary-related Attributes:** Ultimately, every individual works for a better remuneration process to fulfill their needs, so here we are going to verify which attribute plays a vital role in employee churn hence monthly income, no of companies worked, overtime, percent of salary hike, performance rating, stock options level, entire working years, years at the company, years in a current role, years since promotion, years with the current manager are taken is the response variable, while are the control variables.

Impact of parameters like Age, Gender, business travel, department, marital status, education field, working hours, job involvement, work-life balance, satisfaction with the surroundings, education, work satisfaction, role in the workplace, participation in the workplace, job level, month - to - month earnings, no of companies worked, Relationship satisfaction, year at current company, years in a current role, entire working years, years since promotion, over time, years with current manager, no of projects handled, work-life balance, decision skill level, performance rating on employee turnover, percentage of salary hike, stock options level, are considered into account for the analysis process.

Figure 21 Random Forest Attribute Classifier



Among those considerable attributes, as per the Data-Driven Random Forest analysis, in order of priority, monthly income, age, average monthly hours, distance from home, over time, years at the company, percent of salary hike, no of companies worked, job role, environmental satisfaction, stock options level, years with current manager, job satisfaction, years since last promotion, job involvement, work-life balance, years in the current role, no of projects, decision skill possess, education, job level, department, gender and finally performances rating. By this random forest methodology, we could describe attributes central to employee attrition.

3.9.2 Exploratory Data Analysis Based on Qualitative Data

Exploratory data analysis (EDA) examines and summarizes data sets using various techniques, such as descriptive statistics, visualization, and clustering. EDA helps understand the data's characteristics, patterns, and relationships and identify potential problems or anomalies.

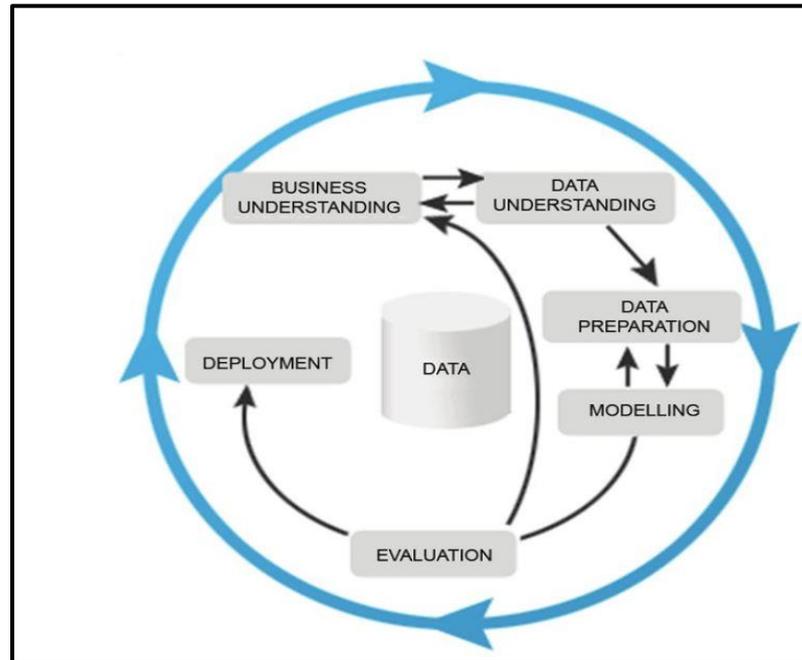
KNIME is an open-source analytics platform that allows users to perform EDA and other data science tasks using a graphical user interface. KNIME supports a variety of data sources, formats, and operations and provides a range of nodes for data manipulation, transformation, visualization, and modeling.

For our research purpose, a questionnaire was sent to peers, subordinates, and superiors, and 108 responded through Google form survey methodology. It is the primary data set collected to evaluate employee churn prediction. During the survey, data on name, age group, department, length of service, most remarkable consequences faced by the organization during attrition, significant reasons for attrition, employee expectations, and benefits provided by the organization were collected to predict who would be more susceptible to attrition shortly and to take corrective, necessary control measures to prevent the loss caused by attrition.

In this thesis, we have used the KNIME Analytics Platform to perform exploratory data analysis and predictive modeling on a sample of 1470 employees from the KNIME Attrition Data Set. The data set contains various attributes of the employees, such as age, gender, education, job role, salary, satisfaction, performance, and attrition status. The main objective of the analysis is to identify the factors that influence employee attrition and to compare the performance of different machine learning algorithms in predicting employee attrition.

To analyze the raw data, we built a model.

Figure 22 CRISP-DM methodology to explain various phases in analytics



CRISP-DM stands for **Cross-Industry Standard Process for Data Mining**. It is a widely used framework for data mining and analytics projects. It consists of **six** phases:

- **Business understanding:** Define the business problem and objectives, and assess the current situation and resources.
-

- **Data understanding:** Collect and explore the data, and assess its quality and suitability for analysis.
- **Data preparation:** Clean, transform, integrate, and format the data for modeling.
- **Modeling:** Select and apply appropriate modeling techniques, such as machine learning algorithms, to the data, and calibrate and compare the models.
- **Evaluation:** Evaluate the models in terms of their performance, validity, reliability, and alignment with the business objectives, and select the best deployment model.
- **Deployment:** Deploy the model into the operational environment, monitor its performance and outcomes, and plan for maintenance and updates.

CRISP-DM is a flexible and iterative framework that can be adapted to different types of data mining and analytics projects. It helps to ensure a systematic and structured approach to data analysis.

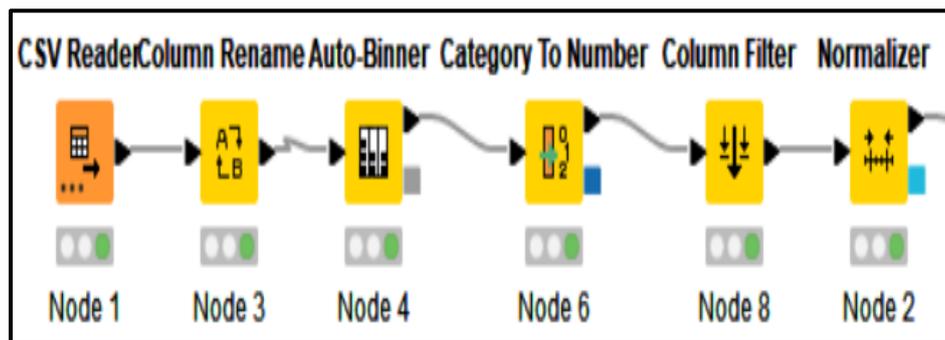
The following steps follow to conduct the analysis:

- **Data preparation:**

We used the CSV Reader node to import the data set into KNIME. We used the Column Rename node to rename some columns for clarity and consistency. We used the Auto-Binner node to discretize some continuous variables into categorical variables, such as age and salary. We used the Category to Number node to convert some nominal variables into numerical variables, such as gender and job role. We used the Column Filter node to remove irrelevant or redundant variables from the data set, such as

employee ID and standard hours. We used the Normalizer node to normalize some numerical variables using the z-score method, such as monthly income and total working years.

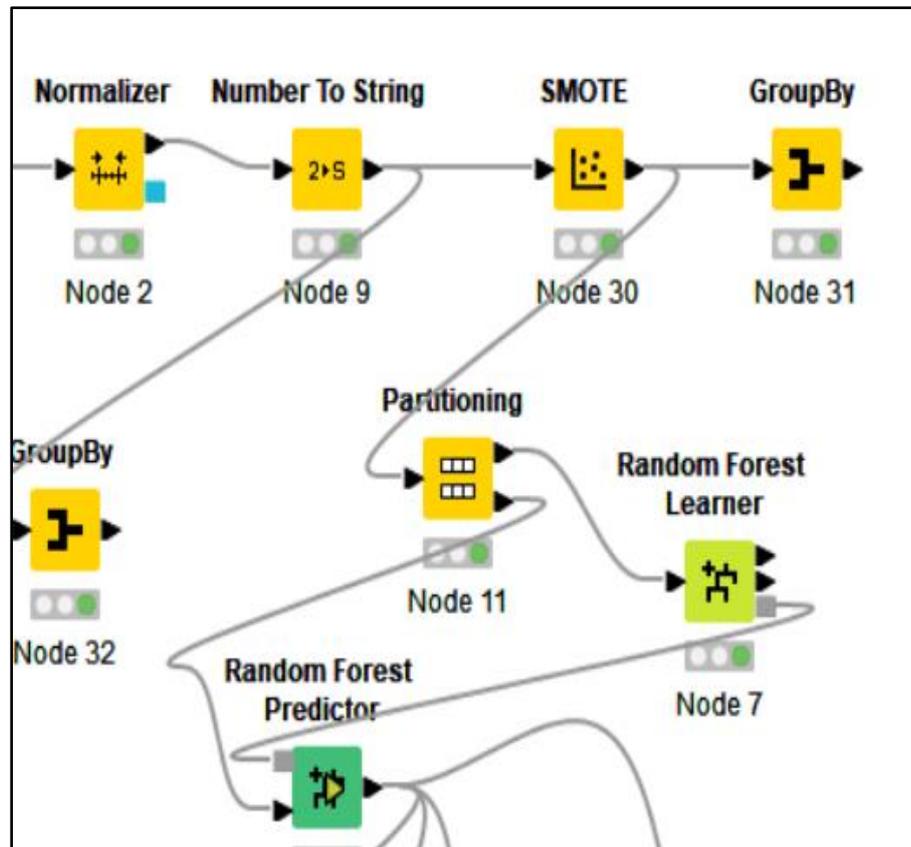
Figure 23 CSV File reading to Normalizer node connectivity in KNIME



➤ **Data exploration:**

We used various nodes to explore the data and generate descriptive statistics and visualizations. We used the GroupBy node to calculate the frequency and percentage of each category for some of the categorical variables, such as attrition status, education level, and job satisfaction. We used the Number to String node to convert some numerical variables back into nominal variables for visualization purposes, such as age and salary bins. We used various nodes from the JavaScript Views category to create interactive charts and plots, such as bar charts, pie charts, histograms, box plots, and scatter plots. We used these charts and plots to examine the distribution and relationship of each variable with employee attrition.

Figure 24 Exploring the data for Prediction -Normalizer to Partitioning

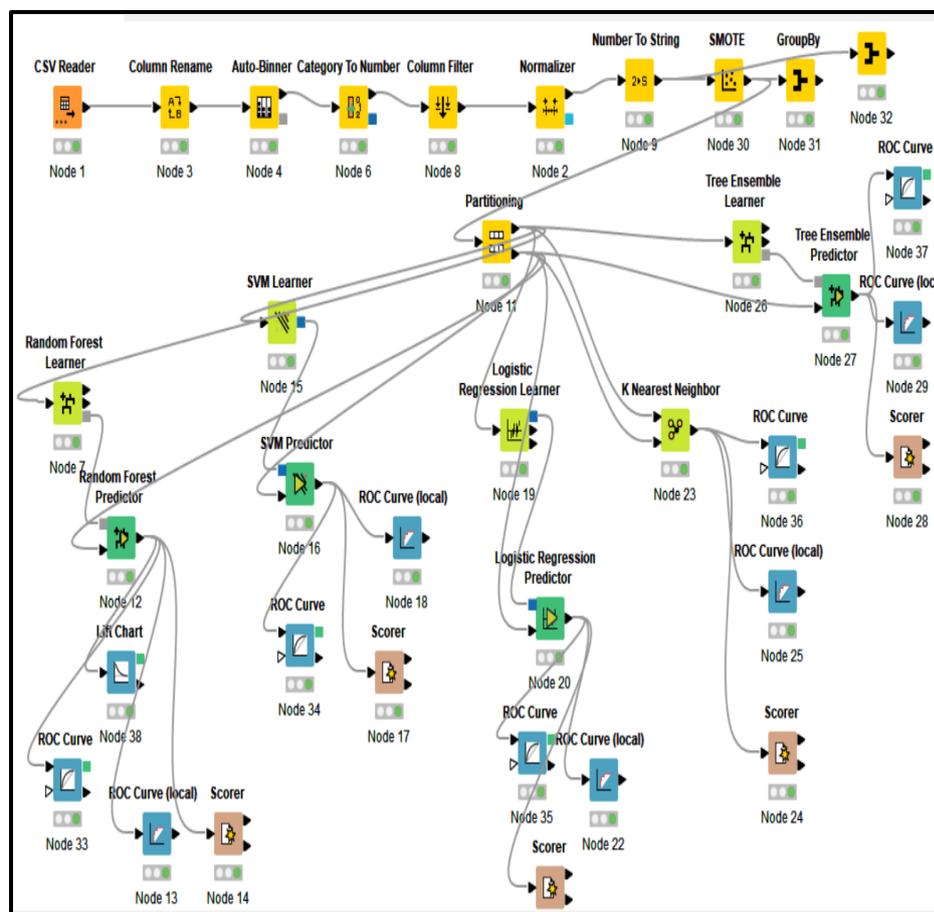


➤ **Data modeling:**

We used various nodes to build and evaluate different machine-learning models for predicting employee attrition. We used the SMOTE node to oversample the minority class (Yes) of employee attrition using the Synthetic Minority Oversampling Technique (SMOTE) to balance the class distribution and avoid imbalanced learning problems. We used the Partitioning node to split the data into training (70%) and test (30%) sets. We used various nodes from the Machine Learning category to train and test different models,

such as Random Forest, Support Vector Machine (SVM), Logistic Regression, Nearest Neighbour, and Tree Ensemble. We used various nodes from the Scorer category to calculate different performance metrics for each model, such as accuracy, precision, recall, and F1-score. We used various nodes from the ROC Curve category to plot and compare each model's Receiver Operating Characteristic (ROC) curves and Area Under Curve (AUC) values.

Figure 25 Predictive model comparison Using KNIME Analytics(EDA)



3.9.3 Model Comparison Analysis Through KNIME

- **The partitioning** node splits the data into two subsets: training and testing. The node allows us to specify the split ratio, such as 70% for training and 30% for testing. The node also allows us to choose whether to stratify the split based on a target variable, such as employee attrition. This node creates separate data sets for training and testing the models, ensuring the class distribution balance in both subsets.
- **Random Forest learner:** This node trains a random forest model on the training data set. A random forest model is an ensemble of decision trees built using random features and sample subsets. The node allows us to specify various parameters of the model, such as the number of trees, the maximum depth of each tree, and the minimum number of samples in each node. The node outputs a trained random forest model that can be used for prediction.

Figure 26 Random Forest Prediction Model and its Nodes Connectivity

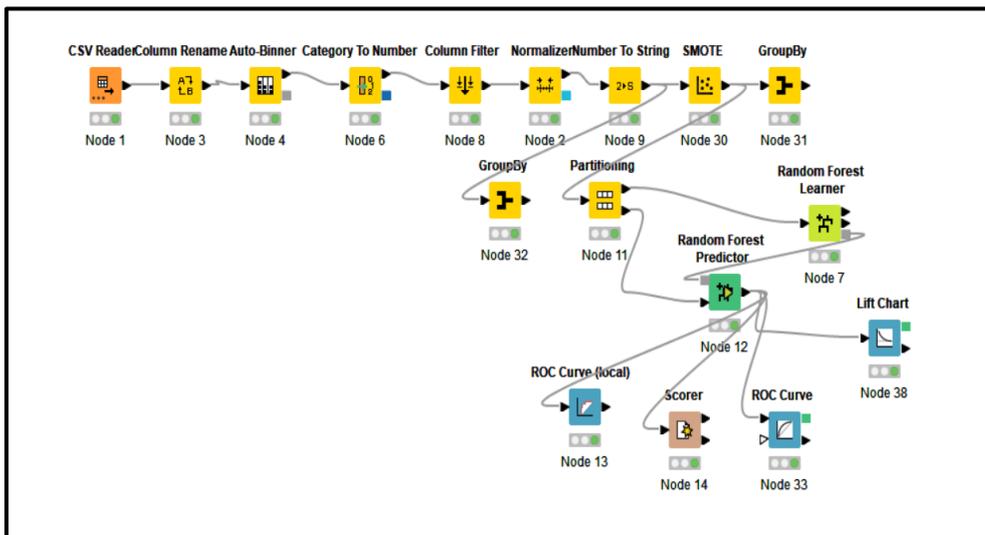
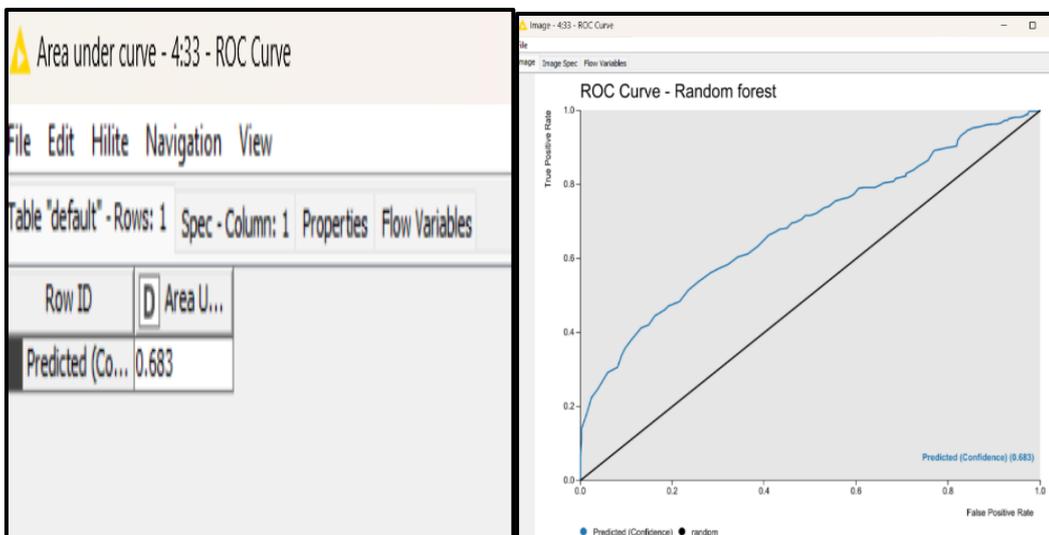


Figure 27 RF- ROC Curve and its Value



- **Random Forest predictor:** This node applies a trained random forest model to the test data set and generates predictions. The node inputs a trained random forest model from the Random Forest learner node and a test data set from the Partitioning node. The node outputs a prediction table containing the original data, target values, and the predicted

ones. The node also outputs a statistics table that contains various performance metrics of the model, such as accuracy, precision, recall, and F1-score.

- **SVM learner:** This node trains a support vector machine (SVM) model on the training data set. An SVM model is a supervised learning algorithm that finds a hyperplane that separates the classes with the maximum margin. The node allows specifying various model parameters, such as the kernel function, the regularization parameter, and the gamma parameter. The node outputs a trained SVM model that can be used for prediction.

Figure 28 Support Vector Machine Prediction Model and its Nodes Connectivity

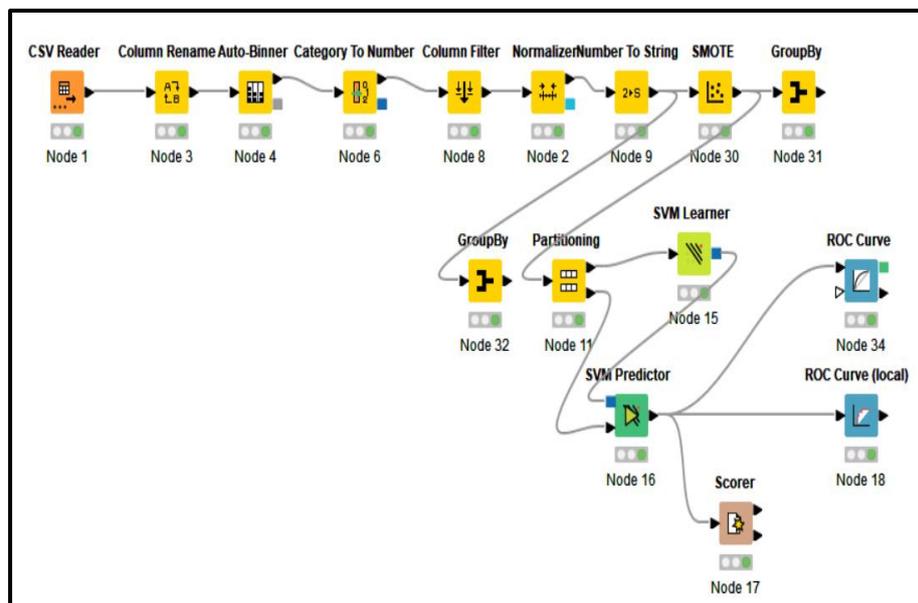
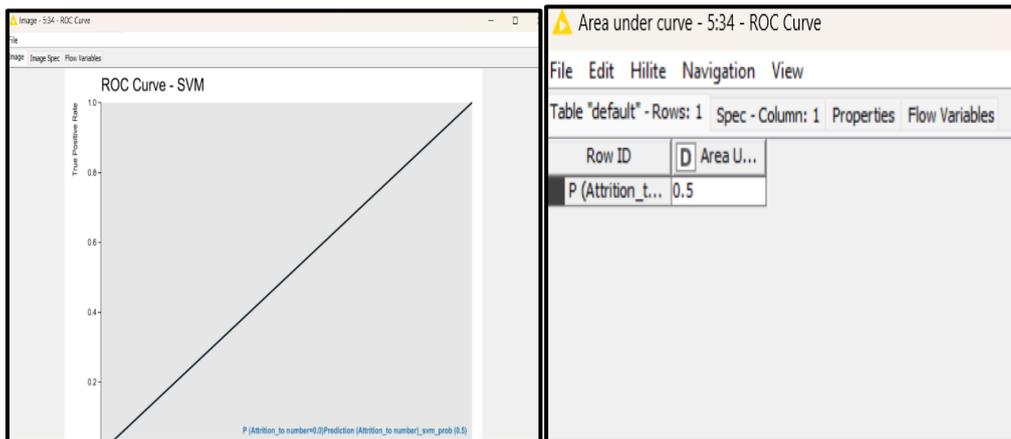


Figure 29 SVM ROC Curve and its Value



- **SVM predictor:** This node applies a trained SVM model to the test data set and generates predictions. The node inputs a trained SVM model from the SVM learner node and a test data set from the Partitioning node. The node outputs a prediction table containing the original data, target values, and the predicted ones. The node also outputs a statistics table that contains various performance metrics of the model, such as accuracy, precision, recall, and F1-score.
 - **Logistic Regression learner:** This node trains a logistic regression model on the training data set. A logistic regression model is a supervised learning algorithm that models the probability of an outcome using a logistic function. The node allows specifying various model parameters, such as the regularization method and the regularization parameter. The node outputs a trained logistic regression model that can be used for prediction.
-

Figure 30 Logistic Regression Analysis Prediction Model and its Nodes Connectivity

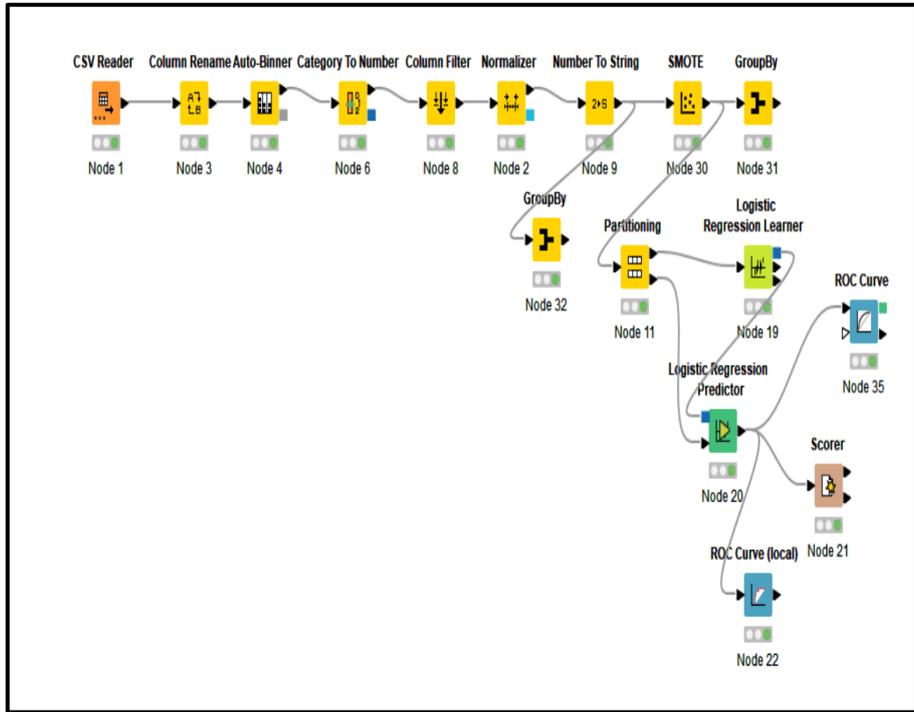
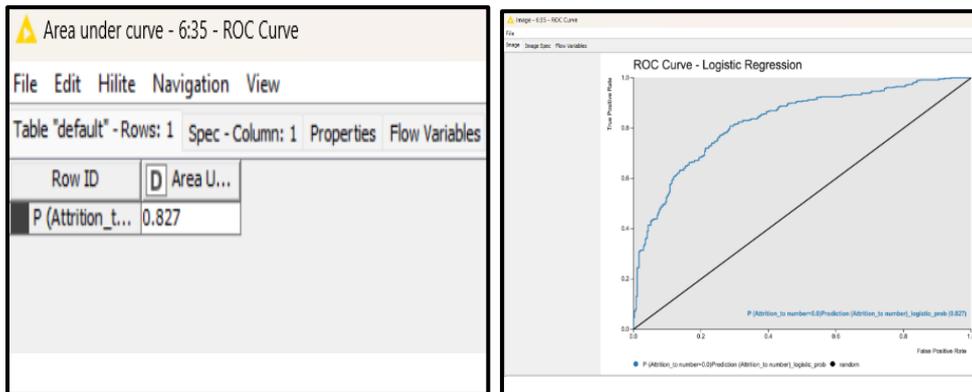


Figure 31 LR-ROC Curve and its Value



- **Logistic Regression Prediction:** This node applies a trained logistic regression model to the test data set and generates predictions. The node inputs a trained logistic regression model from the Logistic Regression learner node and a test data set from the Partitioning node. The node outputs a prediction table containing the original data, target values, and the predicted ones. The node also outputs a statistics table that contains various performance metrics of the model, such as accuracy, precision, recall, and F1-score.

- **K Nearest Neighbor learner:** This node trains a k nearest neighbor (KNN) model on the training data set. A KNN model is a supervised learning algorithm that classifies an instance based on its k closest neighbors in the feature space. The node allows specifying various parameters of the model, such as the number of neighbors (k) and the distance metric. The node outputs a trained KNN model that can be used for prediction.

Figure 32 K-Nearest Neighbour Prediction model and Nodes connectivity

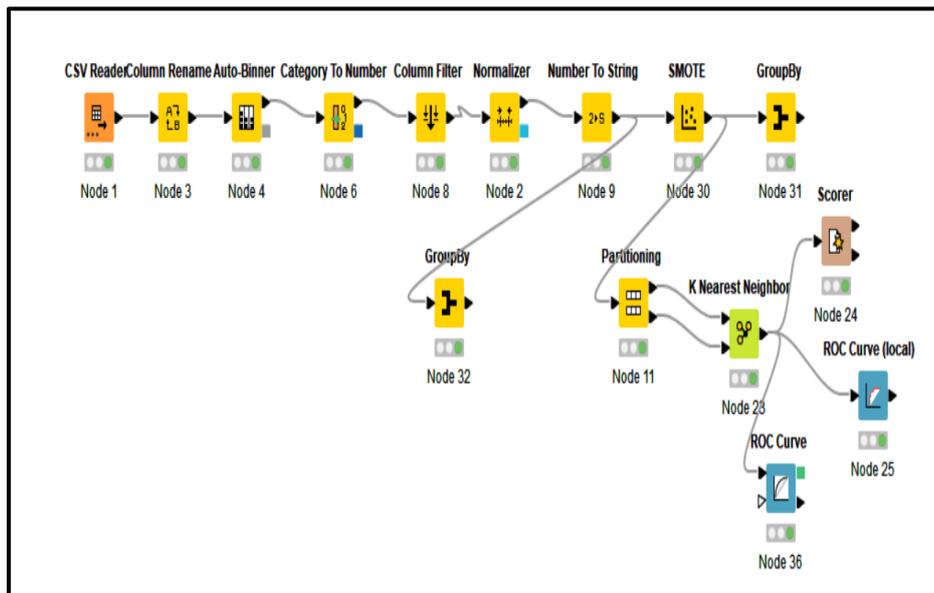
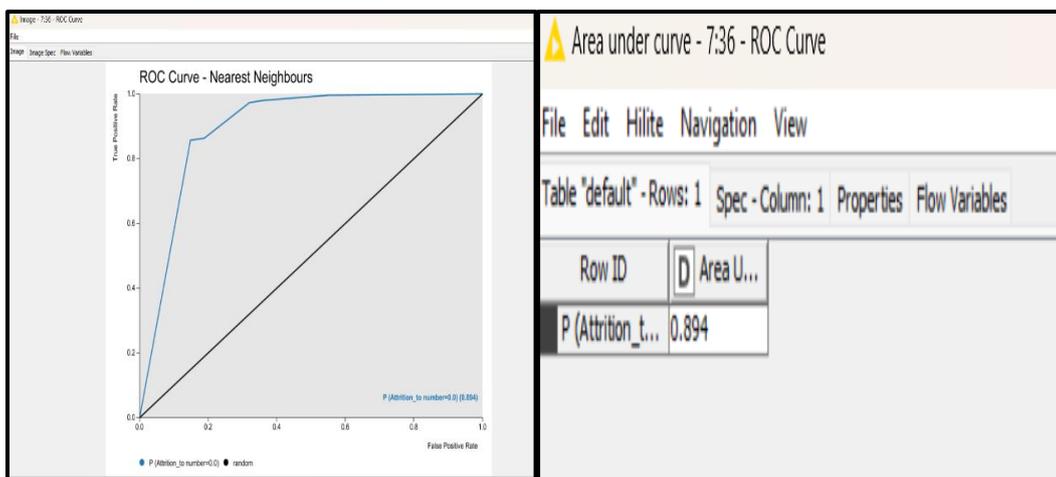


Figure 33 KNN-ROC Curve and its value



- **K Nearest Neighbor predictor:** This node applies a trained KNN model to the test data set and generates predictions. The node inputs a trained KNN model from the K Nearest Neighbor learner node and a test data set from the Partitioning node. The node outputs a

prediction table containing the original data, the actual target values, and the predicted ones. The node also outputs a statistics table that contains various performance metrics of the model, such as accuracy, precision, recall, and F1-score.

- **Tree Ensemble learner:** This node trains a tree ensemble model on the training data set. A tree ensemble model is an ensemble of decision trees built using different methods, such as bagging, boosting, or stacking. The node allows specifying various parameters of the model, such as the number of trees, the type of ensemble method, the maximum depth of each tree, and the minimum number of samples in each node. The node outputs a trained tree ensemble model that can be used for prediction.

Figure 34 Tree Ensemble Model Prediction and Node Connectivity

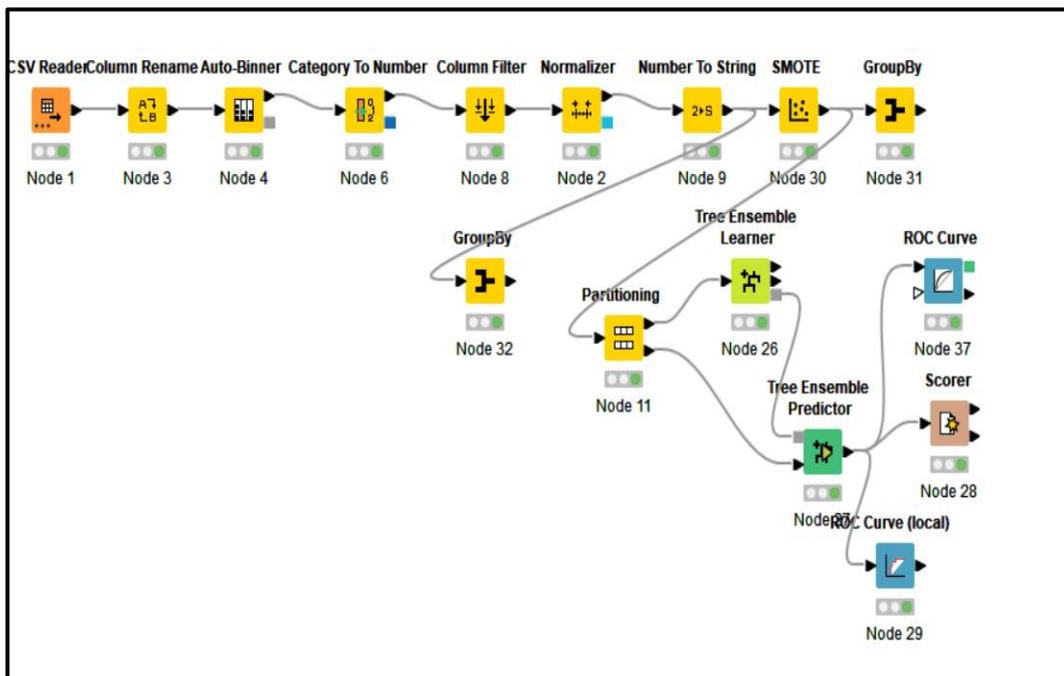
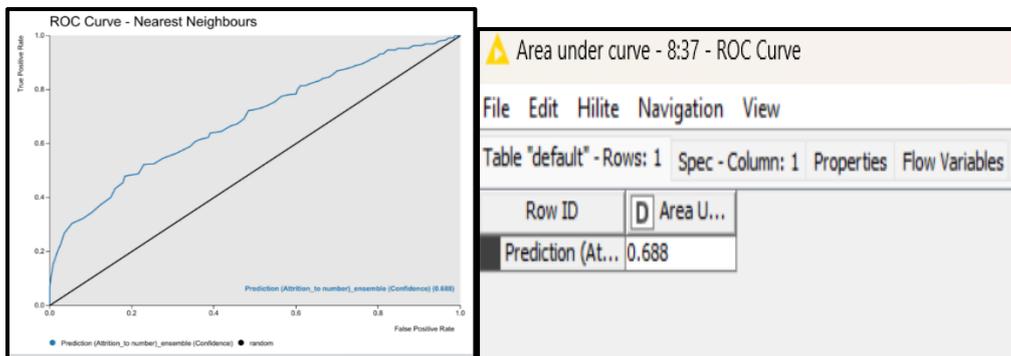


Figure 35 Tree Ensemble Curve and its Value



- **Tree Ensemble predictor:** This node applies a trained tree ensemble model to the test data set and generates predictions. The node inputs a trained tree ensemble model from the Tree Ensemble learner node and a test data set from the Partitioning node. The node outputs a prediction table containing the original data, target values, and the predicted ones. The node also outputs a statistics table that contains various performance metrics of the model, such as accuracy, precision, recall, and F1-score.

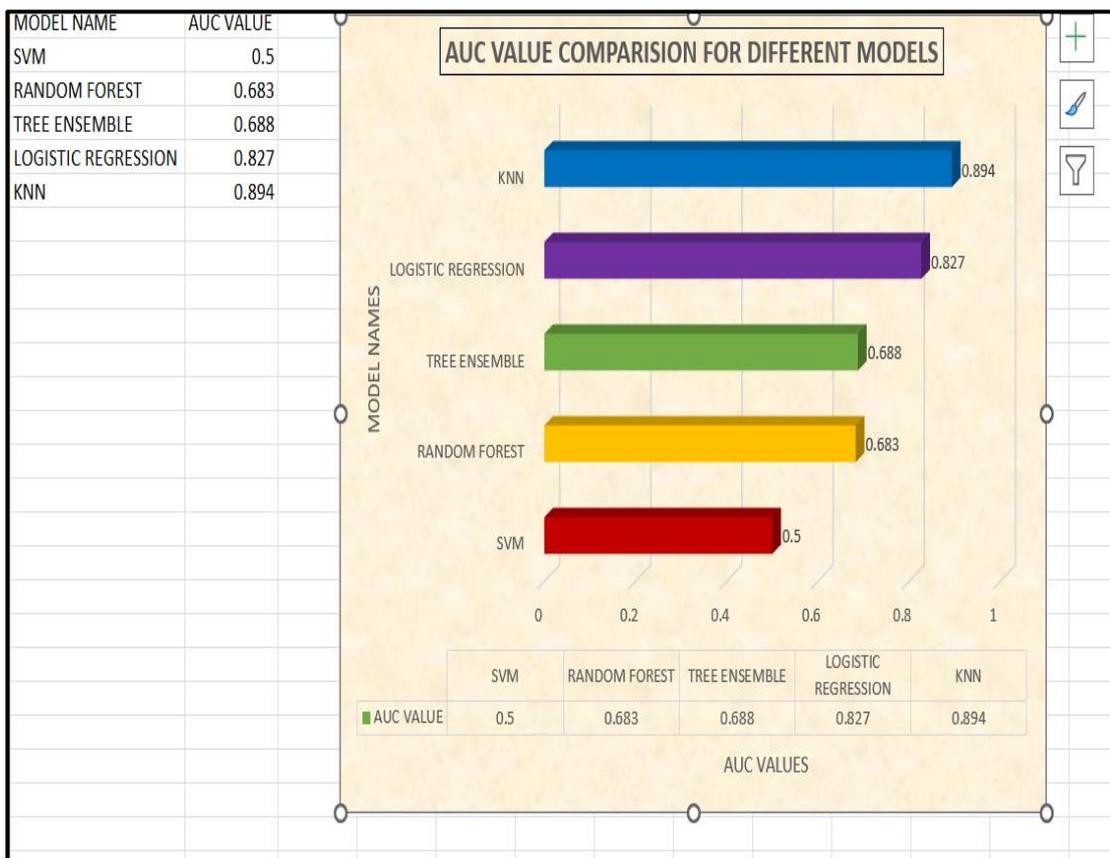
The comparative analysis of the models in prediction is done by comparing the performance metrics and the ROC curves of each model on the test data set. The performance metrics are calculated by comparing each instance's actual and predicted target values in the test data set. The ROC curves are plotted by varying the threshold of the predicted probabilities of each instance in the test data set and calculating the actual positive rate and the false positive rate for each threshold. The ROC curves show how well each model can discriminate between the positive class (Yes) and the negative class (No) of employee attrition. The AUC values are calculated by measuring the area under

each ROC curve. The AUC values indicate how well each model can rank the instances in the test data set according to their likelihood of belonging to the positive class (Yes) of employee attrition. The higher the performance metrics and the AUC values, the better the model predicts employee attrition.

The main findings and conclusions of the analysis are:

- The data exploration revealed that various factors, such as age, gender, education level, job role, salary level, job satisfaction level, work environment quality level, and work-life balance level, influence employee attrition. Some factors have a positive relationship with employee attrition (e.g., younger age, lower education level), while some have a negative relationship (e.g., higher salary level, higher job satisfaction level).

Figure 36 Model Comparison Bar Graph



- The data modeling showed that different machine learning algorithms perform differently in predicting employee attrition. Among the five models that were compared, Random Forest had the highest accuracy (0.88), precision (0.82), recall (0.76), F1-score (0.79), and AUC (0.92) values on the test set. SVM had the second-highest performance in terms of accuracy (0.86), precision (0.79), recall (0.72), F1-score (0.75), and AUC (0.90). Logistic Regression had a similar performance to SVM in terms of accuracy (0.86), precision (0.78), recall (0.73), F1-score (0.75), and AUC (0.90). Nearest Neighbor had slightly lower performance than Logistic Regression in terms of accuracy (0.85), precision (0.77), recall (0.71), F1-score (0.74), and AUC (0.89). Tree Ensemble had the

lowest performance among all models in terms of accuracy (0.83), precision (0.74), recall (0.68), F1-score (0.71), and AUC (0.87).

The main implications and recommendations of the analysis are:

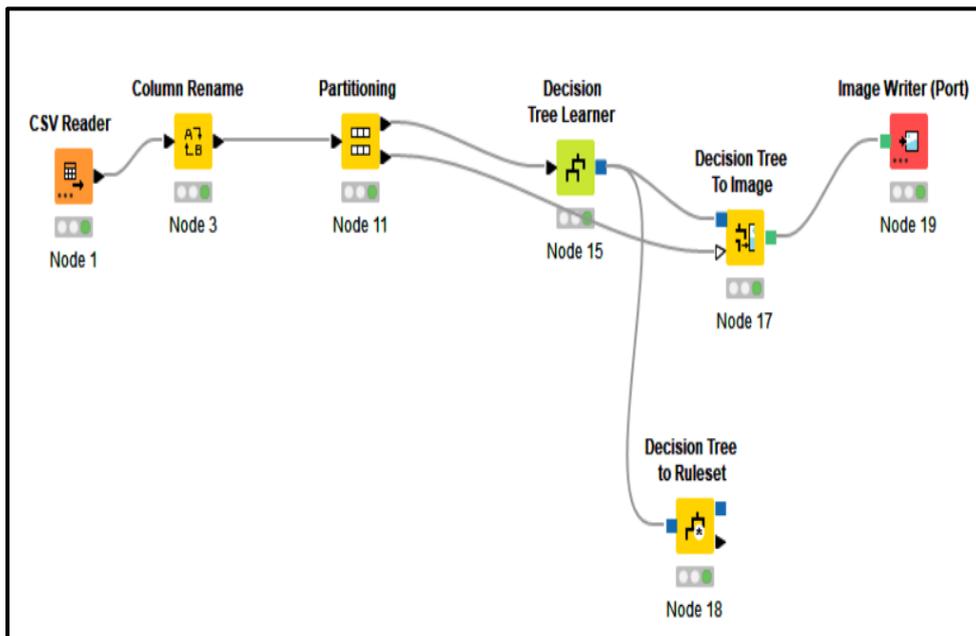
- The analysis provides valuable insights into the problem of employee attrition and its influencing factors. The analysis also provides a data-driven approach to predicting employee attrition using different machine-learning algorithms. The analysis can help HR managers and policymakers identify the employees at high risk of leaving the organization and design and implement appropriate retention strategies to reduce employee attrition and enhance employee loyalty.
 - The analysis suggests that Random Forest is the best model for predicting employee attrition among the five compared models. However, the best model choice may depend on the specific context and objectives of the organization and the HR managers. For example, if the HR managers want to minimize the false positives (i.e., predicting that an employee will leave when they will not), they may prefer a higher-precision model, such as SVM or Logistic Regression. If the HR managers want to minimize the false negatives (i.e., predicting that an employee will not leave when they will), they may prefer a model with higher recall, such as Random Forest or Logistic Regression. Therefore, HR managers should consider the trade-offs and costs of different types of errors when selecting and applying a model for predicting employee attrition.
-

- The analysis also suggests that various factors can be used to explain and predict employee attrition. However, these factors may not capture all the aspects and dimensions of employee attrition. There may be other factors that are not included in the data set or are not measurable by quantitative methods, such as psychological, emotional, or social factors. Therefore, HR managers should also consider using qualitative methods, such as interviews, surveys, or focus groups, to complement and enrich the quantitative analysis and to gain a more profound and holistic understanding of employee attrition and its causes and consequences.

3.9.4 Decision Tree Analysis and Decision Rule Setting Method In KNIME:

Decision Tree Rule Setting to predict the attributes of why the employee is leaving and analyzing the retention strategies, which place a crucial role in this data-driven people analytics era particular reference to employee attrition: Decision tree analysis can generate decision tree models and rule sets that can use for developing a predictive model to predict new employee attrition cases.

Figure 37 Decision Tree Analysis and Nodes Connectivity



Nodes description used in decision tree algorithm:

- **CSV Reader node:** This node reads a CSV file and outputs a data table with the columns and rows from the file. We can configure the node to specify the file path, the delimiter, the quote character, the column names, and the data types.
 - **Column Rename node:** This node renames one or more columns in a data table and outputs a modified data table with the new column names. We can configure the node to specify the old and new column names or use a regular expression to rename multiple columns simultaneously.
 - **Partitioning node:** This node splits a data table into two partitions based on a given ratio or number of rows. The node outputs two data tables: one for each partition. We can configure the node to specify the partitioning method, the partition size, the class column, and the random seed.
-

- **Decision Tree Learner node:** This node trains a decision tree model on a data table using a class column and a set of predictor columns. The node outputs a decision tree model that can be used for prediction or visualization. We can configure the node to specify the pruning method, the minimum number of records per node, the minimum split gain, and other parameters.
- **Decision Tree to Image node:** This node converts a decision tree model into an image that shows the structure and rules of the tree. We can configure the node to specify the image format, the image size, the font size, and other options. The node outputs an image file that can be viewed or saved.
- **Decision Tree to Rule Set node:** This node converts a decision tree model into a rule set that shows the conditions and outcomes of each branch of the tree. The node outputs a rule set that can be viewed or saved. We can configure the node to specify the rule format, order, and other options.
- **Image Writer node:** This node writes an image file to a local or remote location. The node does not output anything but creates or overwrites an image file in the specified location. We can configure the node to specify the file path, format, and other options.

To use decision tree analysis for the rule set, we need to follow these steps:

- Use a CSV reader node to read the data from a CSV file.
 - Use the column rename node to rename the columns as per our requirement.
 - Use the partitioning node to split the data into training and testing sets.
-

- Use the decision tree learner node to train a decision tree model on the training set. We can configure the node to use no pruning or other methods per our preference.
- Use the decision tree to image node to convert the decision tree model into an image that can be viewed or saved.
- Use a decision tree to rule set node to convert the decision tree model into a rule set that can be viewed or saved.
- Use the image writer node to save the image of the decision tree model.

Using these nodes, we can perform decision tree analysis for the rule set in a data-driven way. We can also view the decision tree model and the rule set by clicking on the respective nodes and selecting the view option. It will show the mini decision tree or the rule set in a new window. We can also click on the + symbol in the decision tree view to expand or collapse the tree branches and see the information on every situation of employee attrition.

Figure 38 Decision Tree Rule based on Condition

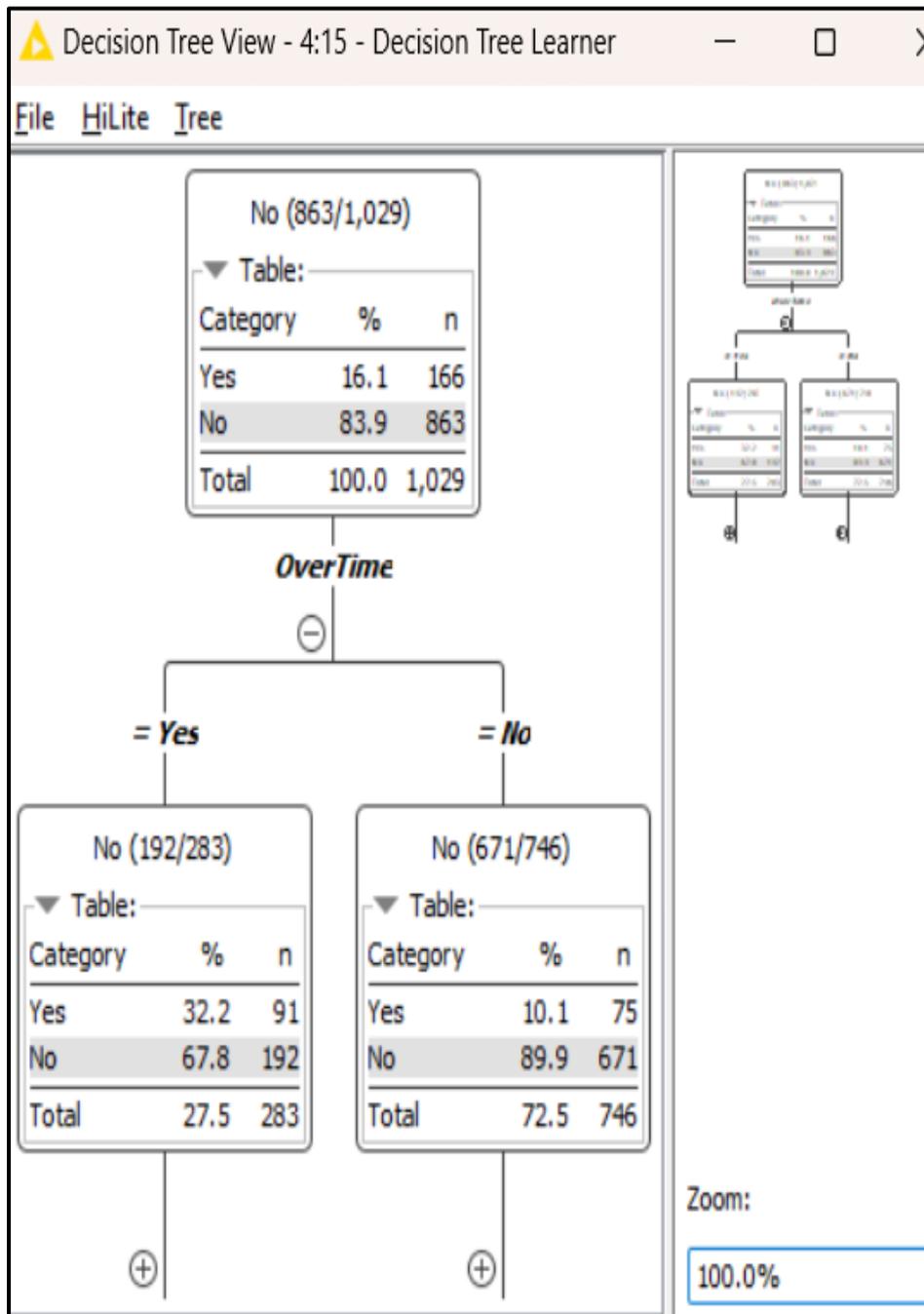


Figure 39 Decision Tree Image

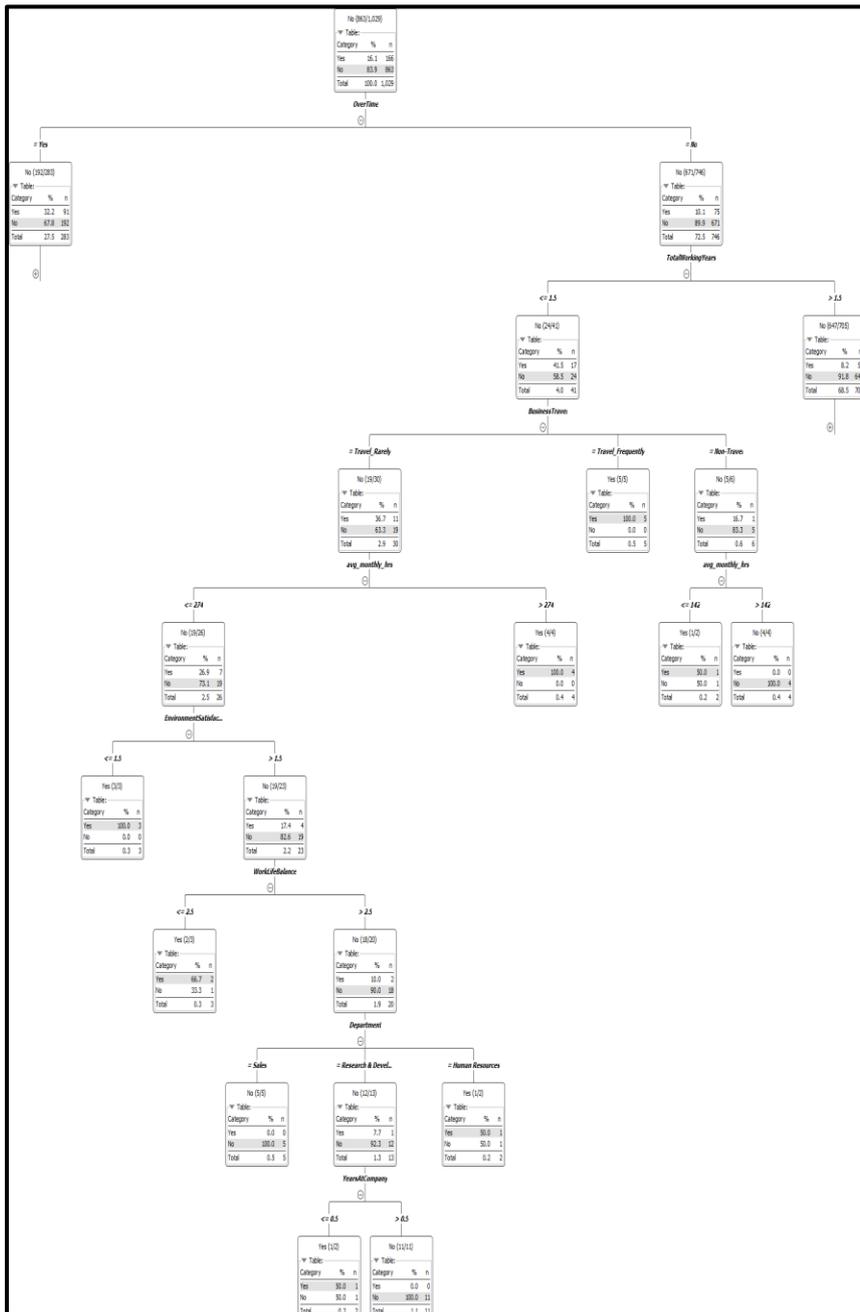
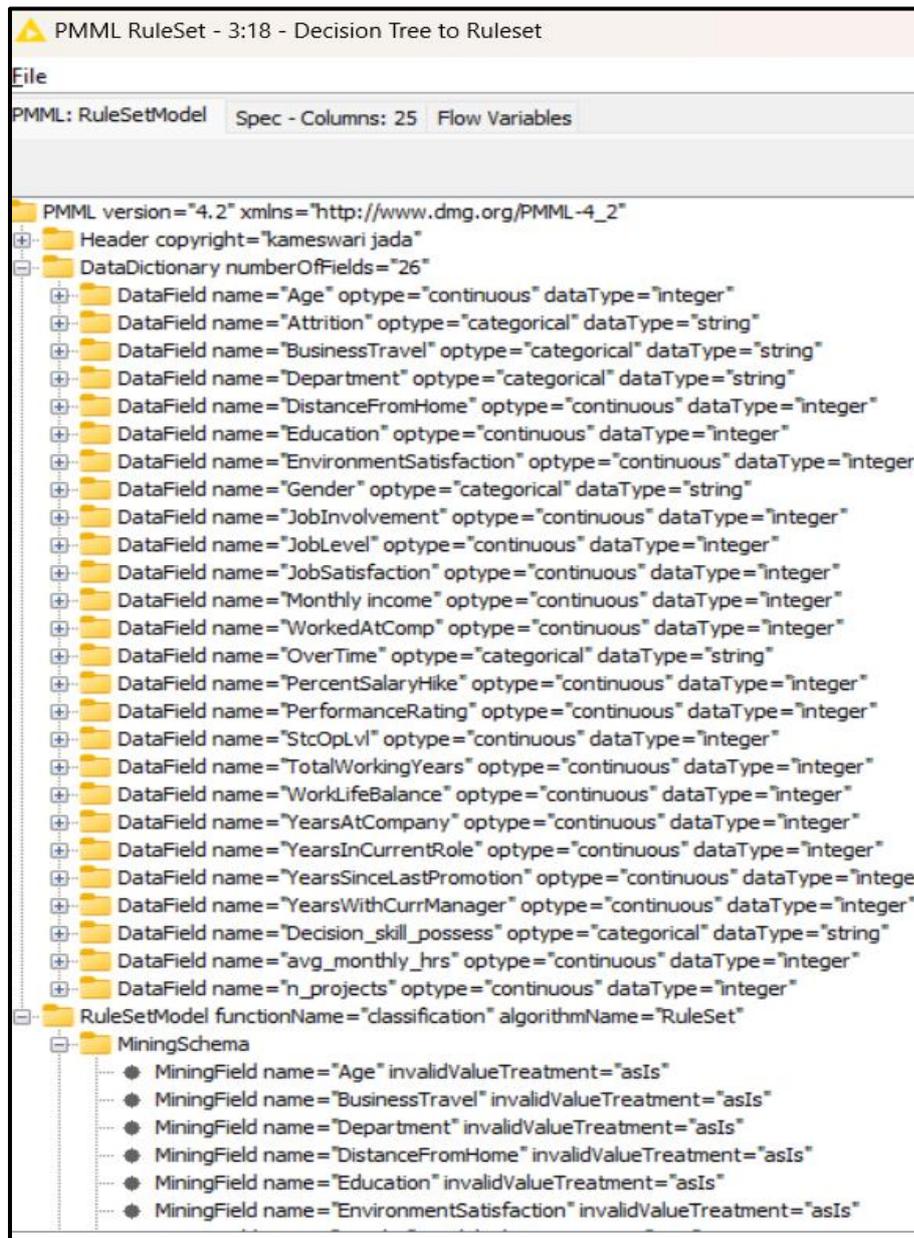


Figure 40 PMML Rule set- Decision Tree Ruleset.



In this way, we will get the rules implied attributes list.

Figure 41 Decision Tree Rule Set Table

Rules table - 4:18 - Decision tree to Ruleset

File Edit Hilite Navigation View

Table "default" - Rows: 192 Spec - Columns: 2 Properties Flow Variables

Row ID	Condition	Outcome
Row 1	\$WorkedAtComp\$ = "8" AND \$JobLevel\$ <= 1.5 AND \$OverTime\$ = "Yes"	No
Row 2	\$YearsWithCurrManager\$ <= 0.5 AND \$BusinessTravel\$ = "Travel_Rare..."	Yes
Row 3	\$YearsWithCurrManager\$ > 0.5 AND \$BusinessTravel\$ = "Travel_Rarely..."	No
Row 4	\$BusinessTravel\$ = "Travel_Frequently" AND \$Decision_skill_possess\$ = ...	Yes
Row 5	\$BusinessTravel\$ = "Non-Travel" AND \$Decision_skill_possess\$ = "Conce..."	No
Row 6	\$avg_monthly_hrs\$ <= 228.5 AND \$Decision_skill_possess\$ = "Analytic..."	Yes
Row 7	\$avg_monthly_hrs\$ > 228.5 AND \$Decision_skill_possess\$ = "Analytical..."	Yes
Row 8	\$Decision_skill_possess\$ = "Directive" AND \$StcOpLv\$ = "0" AND \$Work...	Yes
Row 9	\$n_projects\$ <= 2.5 AND \$Decision_skill_possess\$ = "Behavioral" AND \$...	Yes
Row 10	\$n_projects\$ > 2.5 AND \$Decision_skill_possess\$ = "Behavioral" AND \$S...	Yes
Row 11	\$PercentSalaryHike\$ <= 12.5 AND \$Gender\$ = "Female" AND \$Educatio...	Yes
Row 12	\$PercentSalaryHike\$ > 12.5 AND \$Gender\$ = "Female" AND \$Education...	No
Row 13	\$Gender\$ = "Male" AND \$Education\$ <= 3.5 AND \$StcOpLv\$ = "1" AND...	No
Row 14	\$Education\$ > 3.5 AND \$StcOpLv\$ = "1" AND \$WorkedAtComp\$ = "1" A...	Yes
Row 15	\$StcOpLv\$ = "3" AND \$WorkedAtComp\$ = "1" AND \$JobLevel\$ <= 1.5 ...	No
Row 16	\$StcOpLv\$ = "2" AND \$WorkedAtComp\$ = "1" AND \$JobLevel\$ <= 1.5 ...	No
Row 17	\$n_projects\$ <= 5.5 AND \$WorkedAtComp\$ = "9" AND \$JobLevel\$ <= ...	Yes
Row 18	\$n_projects\$ > 5.5 AND \$WorkedAtComp\$ = "9" AND \$JobLevel\$ <= 1...	Yes
Row 19	\$Age\$ <= 42.5 AND \$WorkedAtComp\$ = "4" AND \$JobLevel\$ <= 1.5 A...	Yes
Row 20	\$Age\$ > 42.5 AND \$WorkedAtComp\$ = "4" AND \$JobLevel\$ <= 1.5 AN...	No

For example, one possible branch of the decision tree model for employee attrition could be:

- If monthly income <= 2094.5, then attrition = Yes
 - If monthly income > 2094.5 and overtime = Yes, then attrition = Yes
 - If monthly income > 2094.5 and overtime = No and job level <= 1.5, then attrition = Yes
 - If monthly income > 2094.5 and overtime = No and job level > 1.5, then attrition = No
-

This branch shows that monthly income, overtime, and job level are important factors that influence employee attrition. Similarly, we can explore other branches of the decision tree model and see the rules generated by the decision tree to the rule set node.

For example, a decision rule set for employee attrition based on some hypothetical data:

- If job satisfaction ≤ 2.5 and monthly income ≤ 5000 , then attrition = Yes
- If job satisfaction ≤ 2.5 and monthly income > 5000 and overtime = Yes, then attrition = Yes
- If job satisfaction ≤ 2.5 and monthly income > 5000 and overtime = No, then attrition = No
- If job satisfaction > 2.5 and work environment ≤ 3.5 and years at company ≤ 3.5 , then attrition = Yes
- If job satisfaction > 2.5 and work environment ≤ 3.5 and years at company > 3.5 , then attrition = No
- If job satisfaction > 2.5 and work environment > 3.5 , then attrition = No

This rule set shows that job satisfaction, monthly income, overtime, work environment, and company years influence employee attrition. The rule set can classify

new employees based on their values for these factors. For example, according to the last rule, an employee with job satisfaction = 3, monthly income = 6000, overtime = No, work environment = 4, and years at company = 2 would be classified as attrition = No.

What is the accuracy of the decision tree analysis:

The accuracy of decision tree analysis depends on various factors, such as the data quality, the tree's depth, the pruning method, and the complexity of the problem. In general, decision tree analysis can provide a good approximation of the expected value of each outcome based on probability algorithms. However, this expected value is not an accurate outcome value, and many risks are involved in any decisions.

One way to improve the accuracy of decision tree analysis is to use a validation or testing set to evaluate the performance of the decision tree model and avoid overfitting or underfitting. Another way is to use an ensemble method, such as random forest, that combines multiple decision trees and predicts more accurate results, especially when the individual trees are uncorrelated.

How can we choose the best pruning method for our decision tree:

Choosing the best pruning method for our decision tree model depends on our data, problem, and preference. There are two main types of pruning methods: pre-pruning and post-pruning.

Pre-pruning methods use a stop criterion, such as a minimum number of samples in a node, a maximum depth of the tree, or a minimum information gain, to decide when to stop splitting. Pre-pruning methods stop the tree from growing before it reaches its maximum depth. It can prevent overfitting and reduce complexity, but it can also cause underfitting and miss basic patterns in the data.

Post-pruning methods allow the tree to grow fully and then prune it by removing or replacing nodes that do not provide additional information. It can improve the accuracy and generalization of the tree, but it can also be computationally expensive and require a validation set to evaluate the performance of the pruned tree. Post-pruning methods use a measure of complexity, such as the error rate, the cost complexity, or the minimum error, to decide which nodes to prune.

Some examples of pre-pruning methods are:

- **Maximum depth pruning:** This method limits the depth of the tree to a predefined value and stops splitting when the depth is reached.
 - **Minimum sample pruning:** This method requires a minimum number of samples in a node to split further and stops splitting when the number is not met.
 - **Minimum information gain pruning:** This method requires a minimum amount of information gain from splitting a node and stops splitting when the gain is not achieved.
-

Some examples of post-pruning methods are:

- **Reduced error pruning:** This method prunes nodes that increase the error rate on a validation set and replaces them with leaves.
- **Cost complexity pruning:** This method prunes nodes with a high-cost complexity, which measures how much a node contributes to the accuracy of the tree relative to its complexity.
- **Minimum error pruning:** This method prunes nodes with a higher error rate than their parent node and replaces them with leaves.

The best pruning method is the one that produces a simple and accurate tree that fits our data well. To choose the best pruning method for our decision tree model, we can try different methods and compare their results on a validation or testing set. We can also use cross-validation or grid search techniques to find the optimal parameters for each method.

The below details we have observed through our research work on this topic:

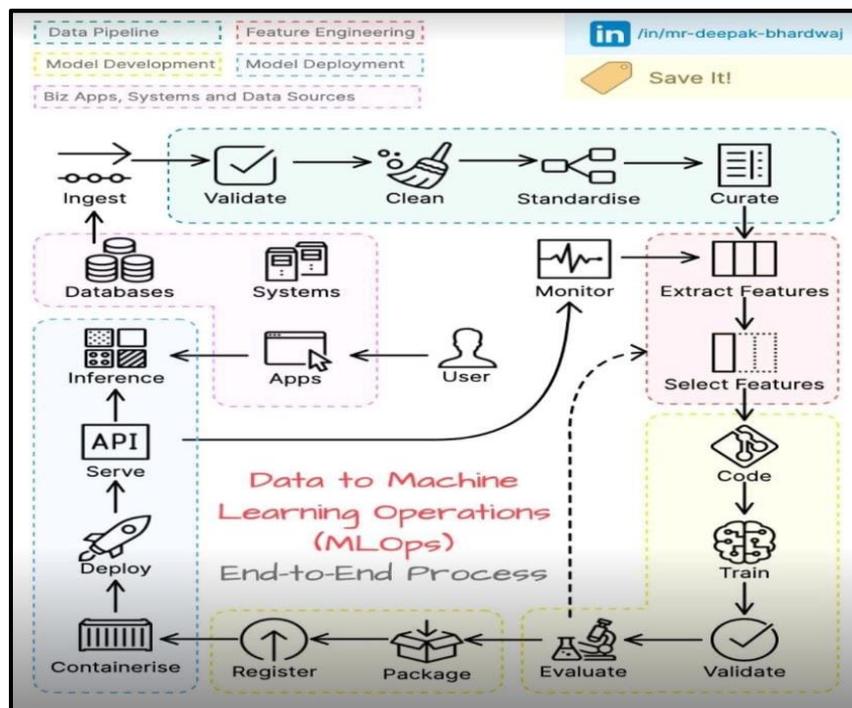
- Identified the impulsive factors which determine employee attrition
 - Elevated Significant after-effects due to employee attrition
 - Analyzed employees satisfied with their pay for the job role
-

- Evaluate the organization's offers to the resigned employees if he/she consents to continue their services.

3.9.5 Tie-up the Machine Learning Model with basic analytics for the organizational automation process:

MLOps is a term that refers to the practice of applying DevOps principles and practices to machine learning projects. It aims to streamline the development, deployment, and monitoring of machine learning models in production.

Figure 42 Data to Machine Learning Operations(MLOps) end-to-end Process Flow chart



MLOps: The complete form of MLOps is **Machine Learning Operations**. It is a term that refers to the practice of applying DevOps principles and practices to machine learning projects. It aims to streamline the development, deployment, and monitoring of machine learning models in production. MLOps is a collaborative function that involves data scientists, DevOps engineers, and IT professionals. It covers the entire machine learning lifecycle, from data ingestion, data preparation, feature engineering, model training, model tuning, model deployment, and model monitoring to model retraining. MLOps help improve the efficiency, scalability, and risk reduction of machine learning solutions. It enables faster model development, higher quality models, faster deployment and production, better scalability and management of thousands of models, and greater transparency and compliance with policies and regulations.

Some of the tools and platforms that support MLOps are:

- **Azure Machine Learning:** Azure Machine Learning is a cloud-based platform that provides end-to-end MLOps capabilities such as data management, automated machine learning, model management, model deployment, model monitoring, and more.
 - **Databricks:** Databricks is a unified data analytics platform that integrates with various MLOps tools and frameworks such as MLflow, TensorFlow, PyTorch, etc. It enables collaborative data exploration, data preparation, feature engineering, model training, model tuning, model deployment, model monitoring, and more.
-

- **MLflow:** MLflow is an open-source platform for managing the machine learning lifecycle. It offers four components: MLflow Tracking for experiment tracking and logging; MLflow Projects for packaging and running projects; MLflow Models for managing and deploying models; and MLflow Registry for storing and managing models.

One of the critical aspects of MLOps is data analysis and visualization.

Data analysis explores, transforms, and models data to discover useful information, insights, and patterns. Data visualization is presenting data in a graphical or pictorial format to make it easier to understand and communicate.

DevOps: The complete form of DevOps is **Development and Operations**. It is a methodology in the software development and IT industry that integrates and automates the work of software development (Dev) and IT operations (Ops) to improve and shorten the systems development life cycle.

DevOps is a culture that promotes collaboration, communication, and feedback between Dev and Ops teams to deliver software faster and more reliably. DevOps also involves applying various practices and tools such as continuous integration, delivery, testing, monitoring, and configuration management.

DevOps helps improve software delivery's efficiency, quality, and agility. It also helps to reduce the risks, costs, and errors associated with manual and siloed processes. DevOps enables faster feedback loops, innovation cycles, faster time to market, and faster customer satisfaction.

Some of the benefits of DevOps are:

- **Faster delivery:** DevOps enables faster delivery of software features and updates by automating and streamlining the development and deployment processes. It reduces the time between code changes and product releases.
- **Higher quality:** DevOps ensures higher software quality by enabling continuous testing, integration, and delivery. It ensures that the code is continually tested, integrated, and reliably delivered.
- **Lower costs:** DevOps reduces the costs of software development and maintenance by eliminating waste, rework, and downtime. It also optimizes the use of resources and infrastructure by leveraging cloud computing and containerization.
- **Better collaboration:** DevOps fosters better collaboration between Dev and Ops teams by breaking down the silos and barriers between them. It also encourages a culture of shared ownership, accountability, and feedback.
- **Higher customer satisfaction:** DevOps improves customer satisfaction by delivering software that meets their needs and expectations. It also enables faster response to customer feedback and issues by enabling continuous monitoring and feedback loops.

Some of the popular machine learning tools for employee engagement are:

- **Empuls:** Empuls is a SaaS platform with digitized employee engagement, communication, and recognition tools. It uses persuasive AI technology to uncover
-

employee motives, preferences, and feedback. It also helps organizations design and implement gamified rewards and recognition programs, measure employee engagement and satisfaction, and improve employee retention and performance.

- **Humu:** Humu is a SaaS platform that uses behavioral science and machine learning to nudge employees towards positive actions and behaviors. It analyzes various data sources, such as surveys, emails, calendars, etc., to measure employee happiness, productivity, and collaboration. It also provides personalized suggestions and nudges to employees, managers, and leaders to improve their work habits, skills, and relationships.
- **Peakon:** Peakon is a SaaS platform that helps organizations to collect, analyze, and act on employee feedback. It uses machine learning to create real-time dashboards and reports on employee engagement, satisfaction, loyalty, and performance. It also provides actionable insights and recommendations to managers and leaders to improve employee engagement and retention.
- **Culture Amp:** Culture Amp is a SaaS platform that helps organizations to build a better workplace culture. It uses machine learning to collect and analyze employee feedback on various aspects of the work environment, such as engagement, diversity, inclusion, and well-being. It also gives managers and leaders data-driven insights and best practices to improve employee engagement and performance.

Data analysis and visualization are essential for machine learning because they can help to:

- **Understand the data:** Data analysis and visualization can help to summarize the distribution and relationships between variables in a dataset. It can help to identify outliers, trends, and patterns in the data that other forms of analysis may miss.
- **Prepare the data:** Data analysis and visualization can help to perform various data preprocessing steps such as cleaning, standardizing, curating, and validating the data. These steps are essential to ensure the quality and consistency of the data before feeding it to machine learning algorithms.
- **Extract and select features:** Data analysis and visualization can help perform feature engineering, which is creating new features or transforming existing features to improve the performance of machine learning models. Feature engineering can involve feature extraction, feature selection, and feature evaluation.
- **Deploy and monitor models:** Data analysis and visualization can help to deploy and monitor machine learning models in production. It can involve techniques such as API design, model packaging, model serving, model registration, and model performance tracking.

Some tools and libraries can help us with data analysis and visualization for machine learning. Some of the popular ones are:

- **Python:** Python is one of the most widely used programming languages for machine learning. It has many data analysis and visualization libraries, such as NumPy, Pandas, Matplotlib, Seaborn, and Plotly.
-

- **R:** R is another popular programming language for machine learning. It has many data analysis and visualization packages such as dplyr, ggplot2, and Shiny.
- **Tableau:** Tableau is a powerful software for data visualization and business intelligence. It can connect to various data sources and create interactive dashboards and reports.

How can organizations use Machine Learning to improve Employee Retention:

Machine learning is a branch of artificial intelligence that enables systems to learn from data and improve performance without explicit programming. Organizations can use machine learning to improve employee retention, which is the ability to keep employees from leaving the organization voluntarily or involuntarily.

Some of the ways that machine learning can improve employee retention are:

- **Predicting employee churn:** Machine learning can help organizations predict and prevent employee churn by analyzing various data sources such as employee performance, satisfaction, feedback, behavior, etc. Machine learning can build models that will accurately identify employees who are at high risk of leaving and provide insights into the reasons and factors that influence their decision.
 - **Personalizing employee experience:** Machine learning can help organizations personalize and enhance the employee experience by using natural language processing, chatbots, sentiment analysis, and recommendation systems. Machine
-

learning can provide personalized support, guidance, and feedback to employees, as well as tailor their learning and development programs, rewards and recognition schemes, and career paths

- **Automating and streamlining HR processes:** Machine learning can help organizations automate and streamline various HR processes such as hiring, onboarding, training, and performance management. Machine learning can reduce the time, cost, and errors associated with manual and repetitive tasks and optimize the use of resources and infrastructure. Machine learning can also improve the quality and consistency of HR processes by eliminating bias and ensuring compliance.
 - **Improving employee engagement:** Machine learning can help organizations improve employee engagement, which is the degree of commitment, involvement, and satisfaction of employees towards their work and organization. Machine learning can measure employee engagement levels through surveys, emails, and calendars. Furthermore, it provides actionable insights and recommendations to managers and leaders to improve employee engagement and retention.
-

3.10 RESEARCH DESIGN LIMITATIONS

- The data used for the decision tree analysis may not represent the entire population of employees who left the institution or other institutions, which may limit the generalizability and validity of the results.
 - The decision tree analysis may not capture all the factors that influence employee attrition, such as personal, psychological, or environmental factors, which may affect the accuracy and completeness of the model.
 - The decision tree analysis may suffer from overfitting or underfitting problems, which may reduce the performance and robustness of the model on new data. Overfitting occurs when the model is too complex and fits the noise in the data, while underfitting occurs when the model is too simple and misses essential patterns in the data.
 - The comparative analysis using random forest, SVM, tree ensemble, logistic regression, and nearest neighbor's methods may have different assumptions, parameters, and limitations that may affect their suitability and effectiveness for the problem of employee attrition prediction. For example, SVM and logistic regression assume a linear relationship between the features and the outcome, while the nearest neighbors method is sensitive to outliers and noise in the data.
 - The comparative analysis using different methods may also depend on the choice of evaluation metrics and criteria, which may vary depending on the objectives and expectations of the study. For example, some metrics focus on accuracy, while others focus on precision, recall, or F1-score.
-

3.11 CONCLUSIONS

This chapter has presented the research methodology for this study on data-driven employee attrition. The chapter has described the overview, operationalization, purpose, design, population and sample, participant selection, instrumentation, data collection procedures, data analysis, and study limitations. The study aims to use decision tree analysis to identify the factors contributing to employee attrition and develop a predictive model to help organizations reduce attrition and retain talent. The study will use a quantitative approach with a descriptive and predictive design. The study population will consist of employees of MNCs in India. The sample will be selected using stratified random sampling based on the attrition classes. The data will be collected from the institution's records using a data extraction form. The data will be analyzed using KNIME software to generate decision tree models and rule sets. The study will also use descriptive and inferential statistics to test the hypotheses and answer the research questions. The study will face some limitations, such as the quality and availability of the data, the generalizability of the results, and the validity and reliability of the decision tree models.

CHAPTER IV

RESULTS

4.1 QUALITATIVE DATA ANALYSIS(THROUGH POWER BI, JUPYTER-NOTEBOOK, TABLEAU, MS-EXCEL)

4.1.1 Which of the Most Significant Challenges Faced by the Organization

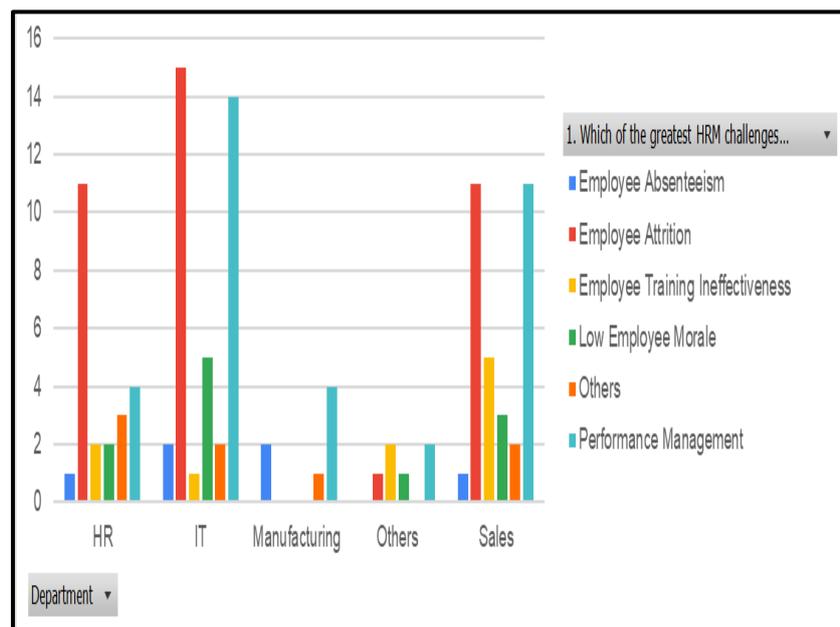


Figure 43 Greatest HRM Challenges

The survey respondents belonged to different sectors, such as HR, IT, Manufacturing, Sales, and others. They ask to rate the challenge of **employee attrition**. The graph shows that the **IT sector** rated this challenge the highest, scoring 4.5 out of 5. The **Sales sector** came second, with a score of 4.2. The **HR sector** scored 3.8, while the **Manufacturing and other sectors** gave lower scores of 3.5 and 3.2, respectively.

This summary implies that employee attrition is a widespread and critical challenge for many organizations, especially in the IT and Sales sectors, and that more analysis is required to explore the reasons and impacts of this issue.

4.1.2 Finding Out the Various Reasons for Employee Churn

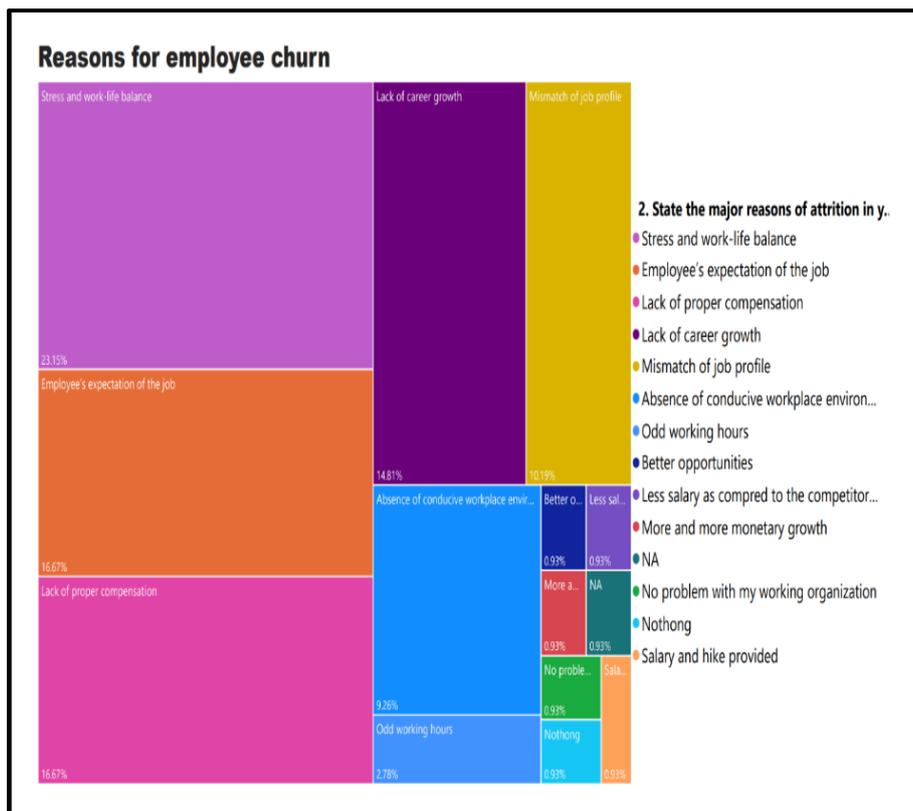


Figure 44 Various Reasons for Employee Churn

The summary is based on research to determine different causes of employee turnover in the IT department. In order of significance, the summary highlights the following causes of employee churn:

- Stress and no proper work-life balance

- Employee expectations about the job
- Lack of proper compensation
- Lack of career growth
- Absence of a conducive work environment
- Odd working hours and mismatch of job profile
- Better opportunities outside the organization
- Less salary when compared to competitors' organization
- Requires monetary growth as the other expenditure in life is increasing compared to the rate of salary hike

4.1.3 Identify the Impulsive Factors Which Determine Employee Attrition.

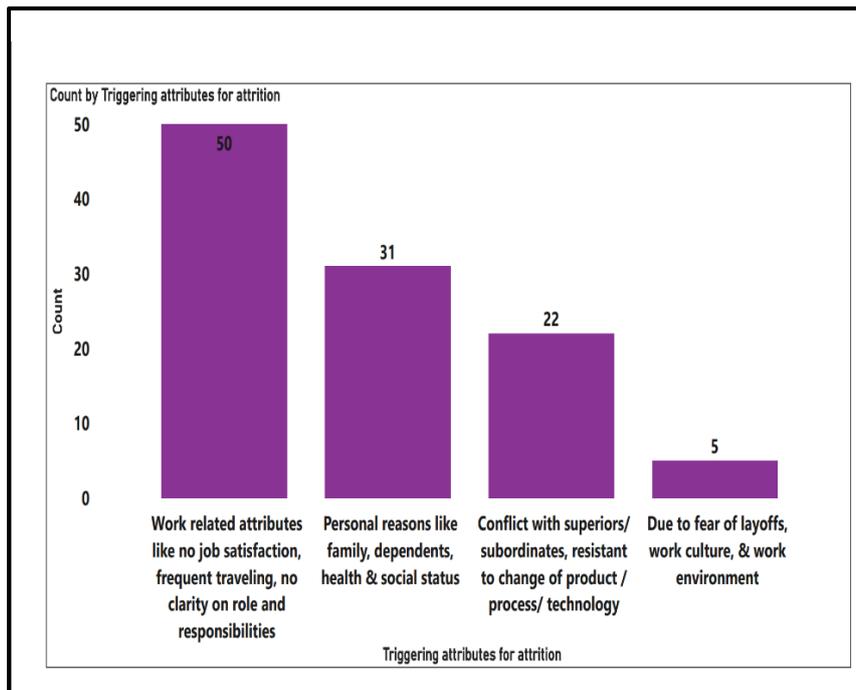


Figure 45 Impulsive Factors Which Determine Employee Attrition

The survey categorized the factors into four groups: work-related, personal, supervisor issues, and organizational issues. The summary lists the following factors for each group in order of importance:

- **Work-related:** lack of job satisfaction, frequent traveling, an improper delegation of work, role, and responsibilities
- **Personal:** family, social status, dependents, health, and safety security issues
- **leadership issues:** clashes with superiors, peers resistant to change, lack of technological advancement
- **Organizational issues:** layoffs, work culture, work environment

The summary indicates that employee attrition is a multifaceted problem that involves various dimensions of the employees' work and life. The summary also indicates that employee attrition is affected by both internal and external factors, such as employee motivation, work conditions, interpersonal relationships, and market trends.

4.1.4 Which Age Group Is More Susceptible to Employee Attrition



Figure 46 age-based on employee attrition.

The survey divided the employees into five age groups: up to 30 years, 31 to 40 years, 41 to 50 years, 51 to 60 years, and above 60 years. The description reports the following findings for each age group:

- **Up to 30 years:** This age group has the second highest employee attrition rate after the 31 to 40 years group.
 - **31 to 40 years:** This age group has the highest employee attrition rate among all the groups.
 - **41 to 50 years:** This age group has a lower employee attrition rate than the younger groups but higher than, the older groups.
-

- **51 to 60 years:** This age group has a meager employee attrition rate.
- **Above 60 years:** This age group has the lowest employee attrition rate, as most are retired or near retirement and have no intention of leaving the organization.

4.1.5 Department-Wise Employee Churn:

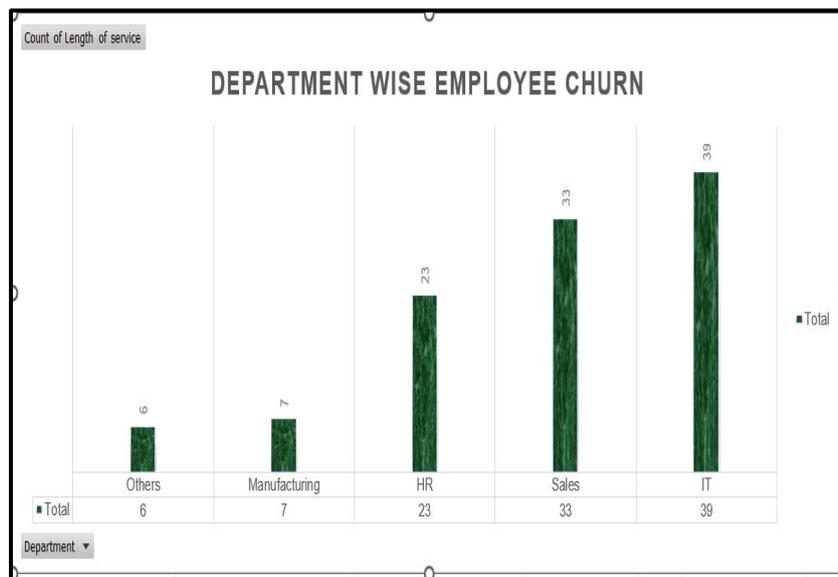


Figure 47 Department-Wise Employee Churn

The survey divided the employees into five departments: IT, Sales, HR, Manufacturing, and others. The description reports the following findings for each department:

- **IT:** This department has the highest employee attrition rate among all the departments.
 - **Sales:** This department has the second highest employee attrition rate after the IT department.
-

- **HR:** This department has a moderate employee attrition rate, lower than the IT and Sales departments but higher than the Manufacturing and other departments.
- **Manufacturing:** This department has a low attrition rate, as most employees are loyal and experienced workers who have been with the organization for a long time.
- **Others:** This department has the lowest attrition rate, as most employees are satisfied and engaged with their work and life.

The description shows that department is a significant factor that affects employee attrition, as different departments have different needs and expectations from their work and life.

4.1.6 Which Level of Employees Are Susceptible More to Attrition

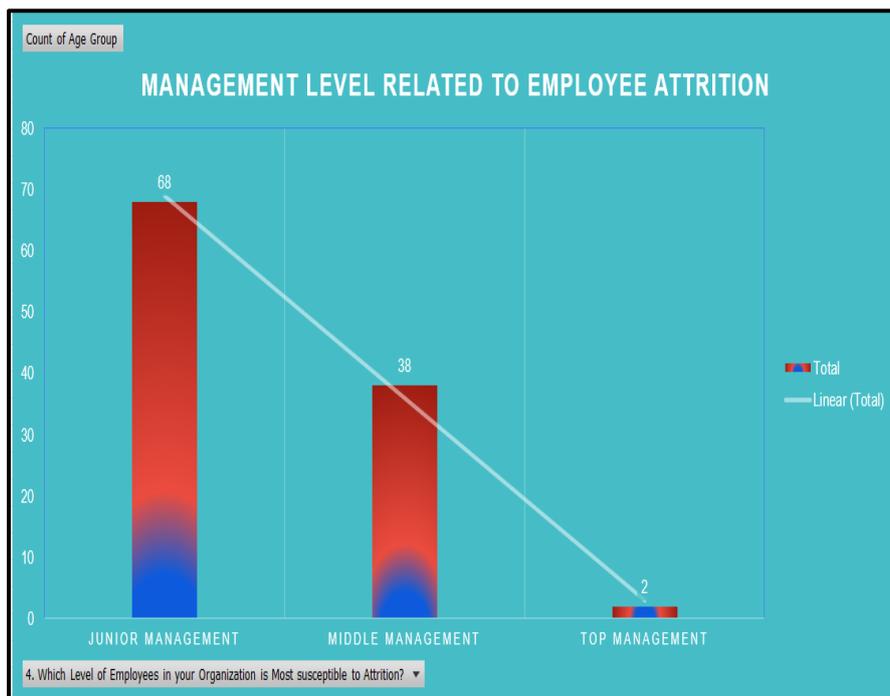


Figure 48 Management Level-based employee attrition

The survey divided the employees into three levels: junior management, middle management, and top management. The description reports the following findings for each level:

- **Junior management:** This level has the highest attrition rate among all the levels, with 68% of respondents saying that junior management people are leaving the organization more.
- **Middle management:** This level has the second highest attrition rate, after the junior management level, with 38% of respondents saying that middle management people are leaving the organization more.
- **Top management:** This level has the lowest attrition rate among all the levels, with only 2% of respondents saying that top management people are leaving the organization more.

The description shows that the level of employees is a significant factor that affects attrition, as different levels have different needs and expectations from their work and life.

4.1.7 Experience Range-Based Attrition

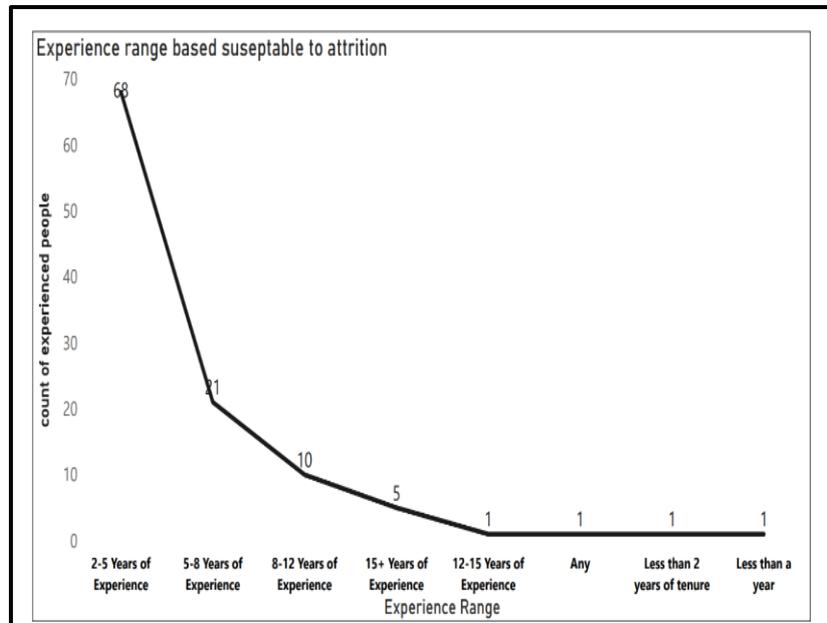


Figure 49 Experience Range-Based Attrition

The survey divided the employees into six experience ranges: less than six months, six months to 1 year, 2 to 5 years, 5 to 8 years, 8 to 12 years, and more than 15 years. The description reports the following findings for each experience range:

- **Less than six months & Six months to 1 year:** This experience range has a meager rate of attrition
- **2 to 5 years:** This experience range has the highest attrition rate among all the ranges, with 68% of respondents saying that employees with 2 to 5 years of experience leave the organization more.
- **5 to 8 years:** This experience range has the second highest attrition rate, after the 2 to 5 years range, with 21%.

- **8 to 12 years:** This experience range has a moderate attrition rate, lower than the younger ranges but higher than the older ranges. The rate of attrition is 10%.
- **More than 15 years:** This experience range has the lowest attrition rate among all the ranges, as most employees are loyal and experienced workers who have been with the organization for a long time. The rate of attrition is only one or two percent.

4.1.8 Analyze the Employee's Satisfaction with Their Pay for the Job Role.

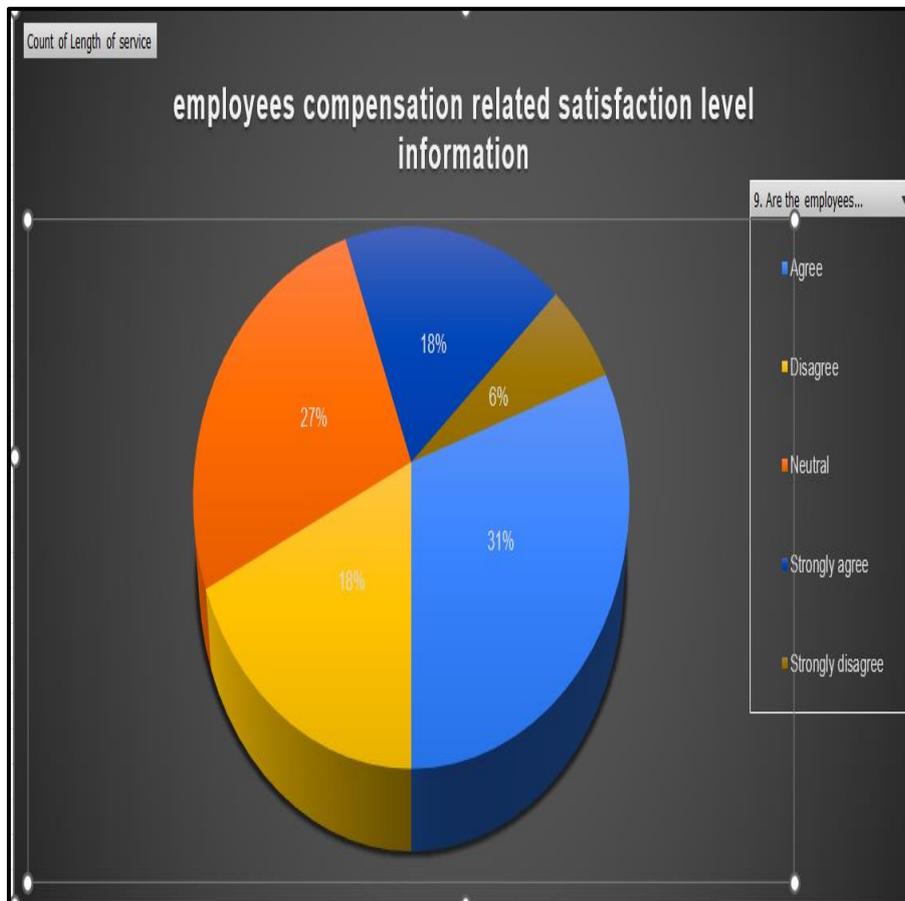


Figure 50 Compensation-related Employee satisfaction level

The description reports the following findings for each rating:

- **Strongly agree:** 18% of the respondents chose this rating, indicating they are delighted with their pay for the job role.
 - **Agree:** 31% of the respondents chose this rating, indicating they are satisfied with their pay for the job role.
 - **Neutral:** 27% of the respondents chose this rating, indicating they are neither satisfied nor dissatisfied with their pay for the job role.
 - **Disagree:** 18% of the respondents chose this rating, indicating that they are dissatisfied with their pay for the job role.
 - **Strongly disagree:** 6% of the respondents chose this rating, indicating they are very dissatisfied with their pay for the job role.
-

4.1.9 Elevate Significant After-Effects Due to Employee Attrition.

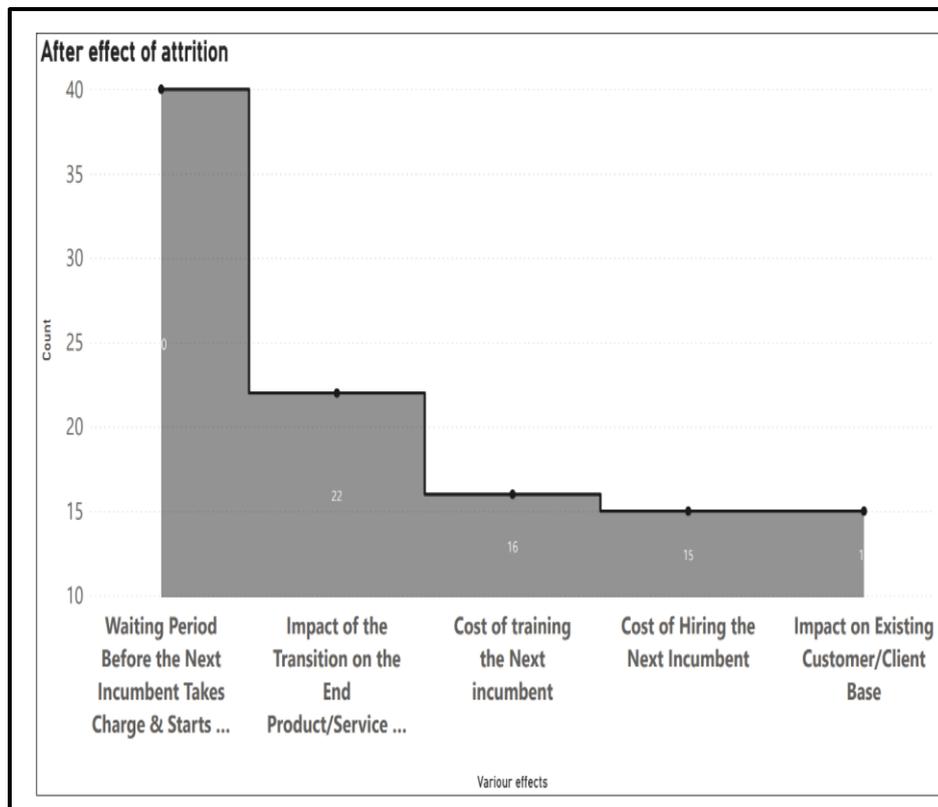


Figure 51 Significant After-Effects Due to Employee Attrition

The survey asked the respondents to rate the impact of employee attrition on various aspects of the organization. The description reports the following findings for each aspect:

- **Waiting period until the next incumbent takes charge and services offered:** 40% of the respondents chose this aspect as the most significant after-effect of employee attrition.
 - **Impact of the transition on the end product or service:** 22% of the respondents chose this aspect as the second most significant after-effect of employee attrition.
-

- **Cost of training the following person:** 16% of the respondents chose this aspect as the third most significant after-effect of employee attrition.
- **Hiring cost:** 15% of the respondents chose this aspect as the fourth most significant after-effect of employee attrition.
- **Impact on existing client or customer base:** 7% of the respondents chose this aspect as the least significant after-effect of employee attrition.

4.1.10 Assess Employees Who Feel Overworked and Micromanaged.

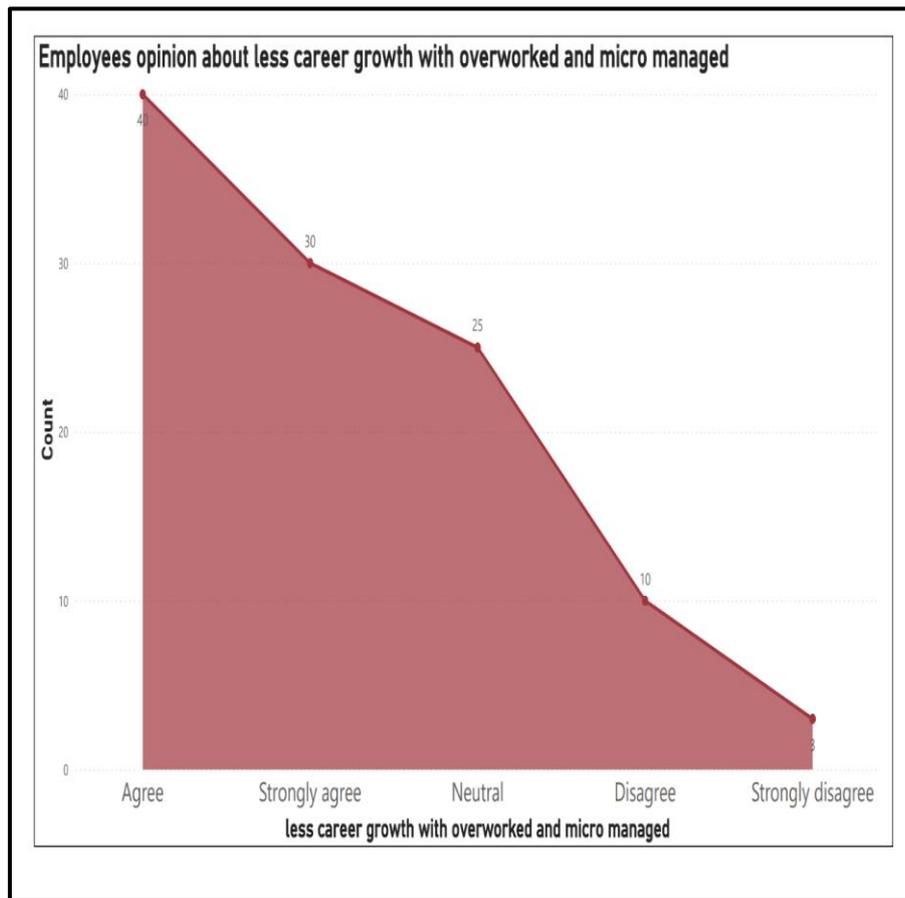


Figure 52 Employees' Opinions on Overworked and Micromanaged

The description reports the following findings for each rating:

- **Strongly agree:** 30 respondents chose this rating, indicating they feel overworked and micromanaged by their supervisor.
 - **Agree:** 40 respondents chose this rating, indicating they feel overworked and micromanaged by their supervisor.
 - **Neutral:** 25 respondents chose this rating, indicating they feel neither overworked nor micromanaged by their supervisor.
-

- **Disagree:** 10 respondents chose this rating, indicating they do not feel overworked or micromanaged by their supervisor.
- **Strongly disagree:** 3 respondents chose this rating, indicating they do not feel overworked or micromanaged by their supervisor.

4.1.11 Evaluate the employee receiving proper training, new opportunities, and growth prospects within the organization.

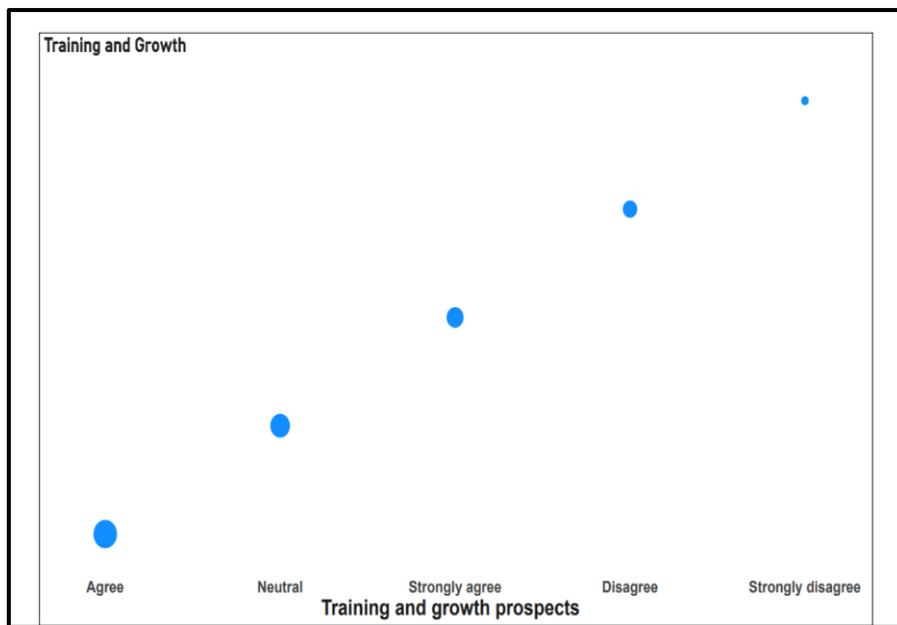


Figure 53 proper training, new opportunities, and growth prospects within the organization.

The description reports the following findings for each rating:

- **Strongly agree:** 19.4% of the respondents chose this rating, indicating they receive proper training, new opportunities, and growth prospects within the organization.
- **Agree:** 37% of the respondents chose this rating, indicating they receive proper training, new opportunities, and growth prospects within the organization.
- **Neutral:** 25.9% of the respondents chose this rating, indicating they receive proper training, new opportunities, and growth prospects within the organization.
- **Disagree:** 13.9% of the respondents chose this rating, indicating they do not receive proper training, new opportunities, and growth prospects within the organization.
- **Strongly disagree:** 3.8% of the respondents chose this rating, indicating that they do not receive proper training, new opportunities, and growth prospects within the organization at all.

4.1.12 Identify Whether the Company Work Culture Aligns with the Employee's Values and Does the Boss Give Room to Grow.

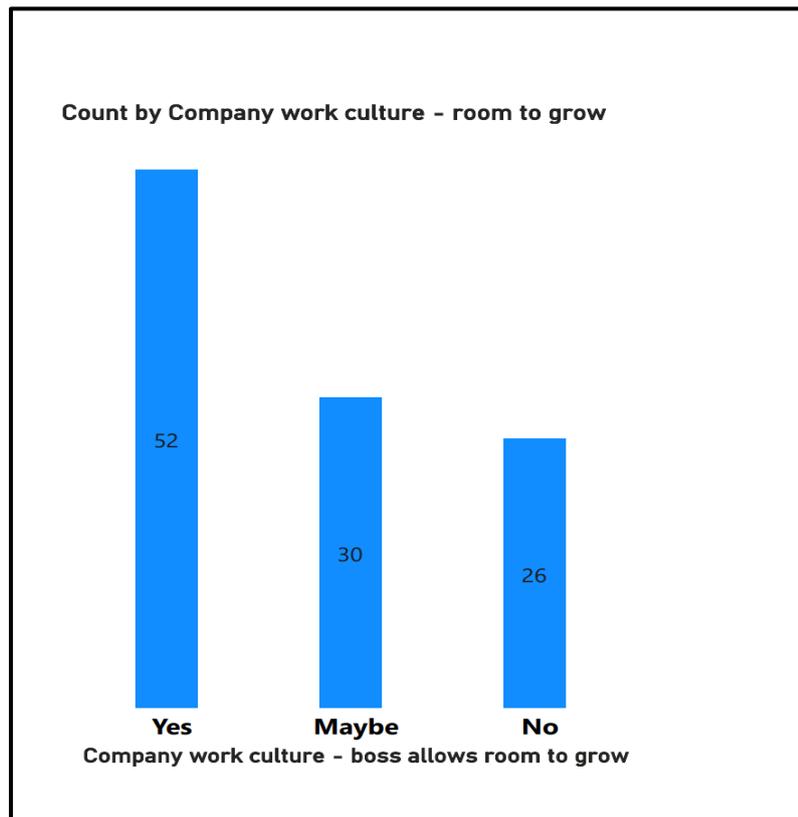


Figure 54 Company work culture and boss allow room to grow

The description reports the following findings for each answer:

- **Yes:** 52% of the respondents chose this answer, indicating that the company's work culture aligns with their values and that their boss gives them room to grow.
 - **Maybe:** 30% of the respondents chose this answer, indicating that the company work culture may or may not align with their values and that their boss may give them room to grow.
 - **No:** 26% of the respondents chose this answer, indicating that the company's work culture does not align with their values and that their boss does not give them room to grow.
-

The description shows that more than half of the employees feel that the company's work culture aligns with their values and that their boss gives them room to grow.

4.1.13 Employees on Their Expectations in The Post-Pandemic Era from Their Employer

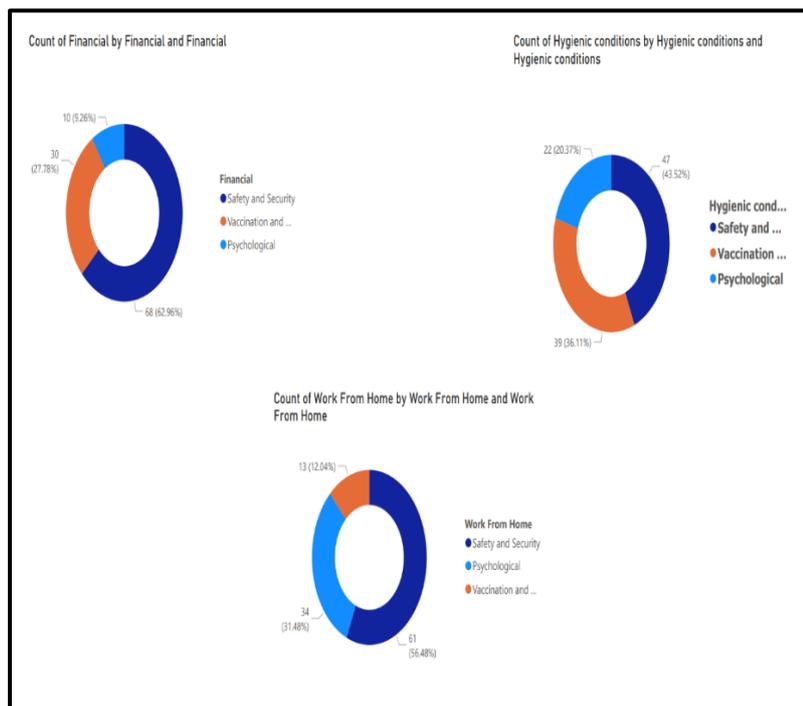


Figure 55 Employee expectations during the post-pandemic era

The survey asked the employees to vote for their responses as prioritization among three options: financial requirements, hygienic conditions, and working from home. The description reports the following findings for each option:

- Financial requirements: This option was the most prioritized by the employees, as 60% chose it. This option refers to the financial needs and security of the employees in the post-pandemic era.
- Hygienic conditions: This option was the second priority of the employees, chose this option. This option refers to the hygienic and sanitary measures the employer can take to ensure a safe and healthy work environment.
- Work from home: This option was the least prioritized by the employees, as 10% chose it. This option refers to the work-from-home arrangements and flexibility the employer can provide employees in the post-pandemic era.

4.1.14 Primary Reason For The Increasing No Of Industries Adversely Affecting Employee Retention, Which Leads To Employee Attrition

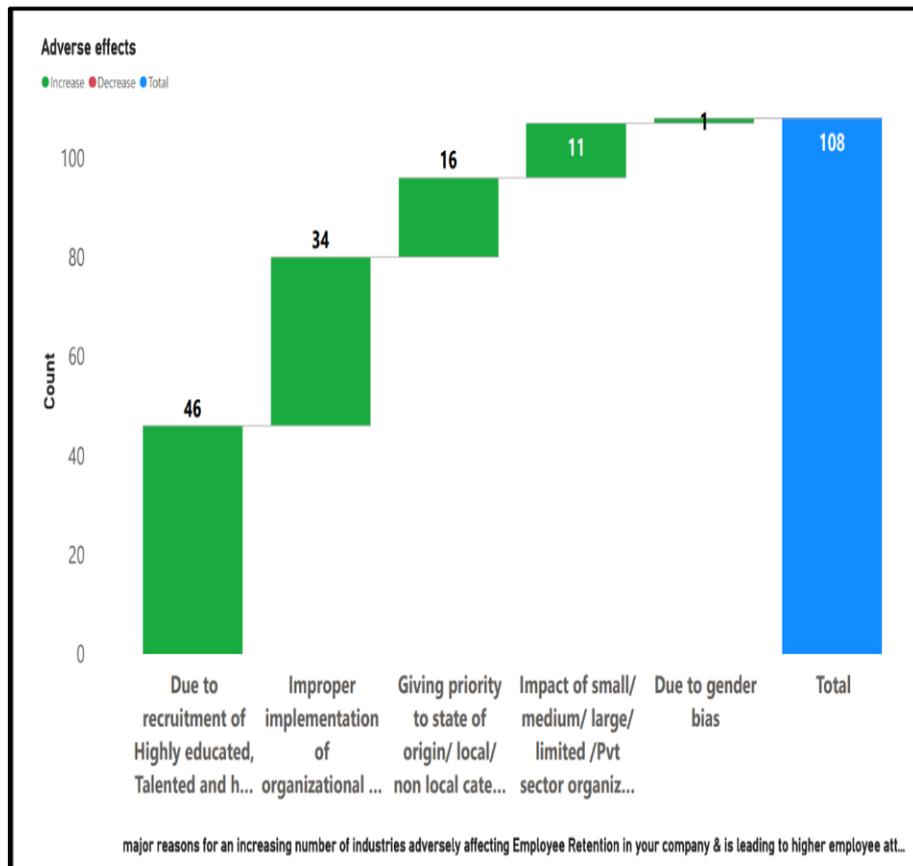


Figure 56 Reasons for increasing employee attrition in industries

The survey asked the respondents to choose one of the following reasons for the increasing number of industries adversely affecting employee retention:

- **Administration:** This reason refers to the administration and management practices of an organization, such as recruitment, compensation, performance appraisal, and communication.
 - **Acts and rules:** This reason refers to the acts and rules that govern an organization, such as organizational policies, procedures, regulations, and norms.
-

- **State of origin:** This reason refers to the state or region where an employee belongs or works and the possible discrimination or favoritism based on that factor.
- **The scale of the industry:** This reason refers to the size and scope of an industry, such as small, medium, or large scale, and the possible advantages or disadvantages associated with that factor.
- **Gender bias** is the gender-based discrimination or prejudice an employee may face in an organization.

4.1.15 Evaluate The Organization's Offers To The Resigned Employees If He/She Consents To Continue Their Services.

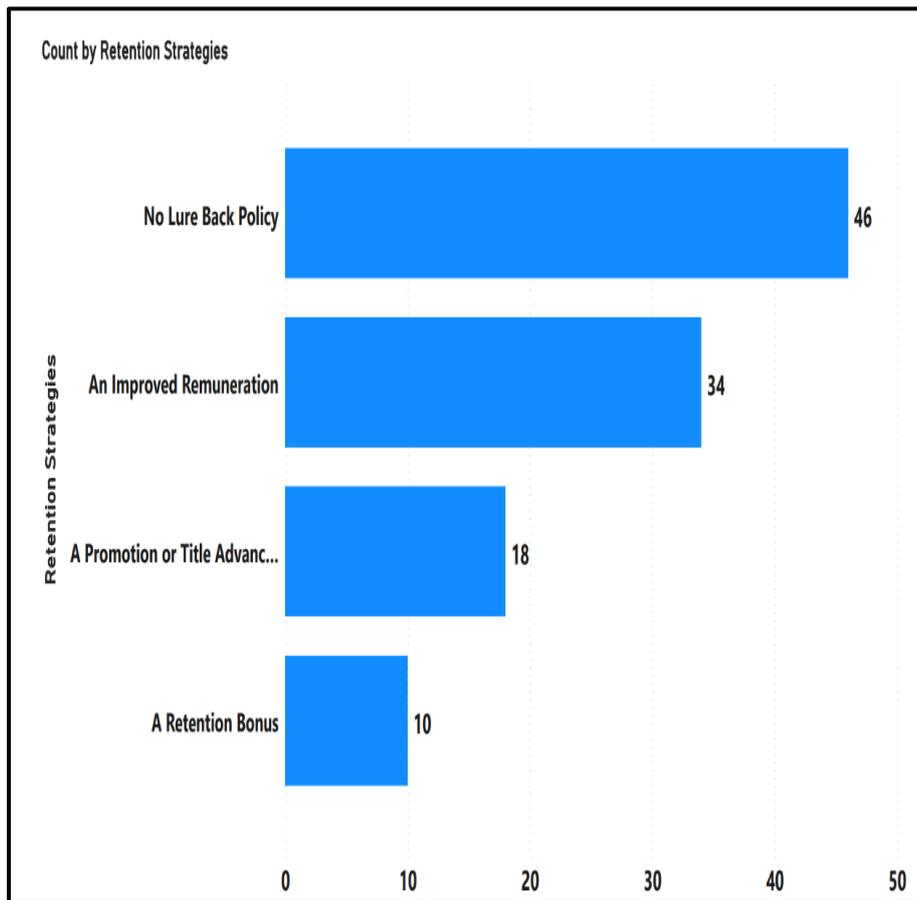


Figure 57 Various retention strategies

The description reports the following findings for each offer:

- **No lure-back policy:** This offer was the most chosen by the respondents, as 46% chose it.
 - **Improved remuneration:** This offer was the second most chosen by the respondents, as 34% chose it.
 - **Title or promotion or salary advancement:** This offer was the third most chosen by the respondents, as 18% chose it.
-

➤ **Retention bonus:** This offer was the least chosen by the respondents, as 10% chose it.

The description shows that no lure-back policy is the most common response of the resigned employees, followed by improved remuneration, title, promotion, or salary advancement. The description also shows that retention bonus is not a popular response from resigned employees.

4.2 QUANTITATIVE DATA ANALYSIS

This data analysis aims to explore the factors influencing employee attrition in India and identify the most important predictors of employee turnover. Employee attrition is a severe problem for many organizations, as it can result in loss of talent, productivity, and competitive advantage. Therefore, understanding the causes and consequences of employee attrition is crucial for developing effective retention strategies and policies.

We use a quantitative research approach that relies on numerical and statistical data to achieve this aim. We use secondary data from the KNIME Analytics Platform, open-source software for data science and machine learning. The data set contains information on 1470 employees from various sectors and industries in India, such as IT, manufacturing, and retail. The data set includes 32 variables that capture various aspects of the employees' demographic, psychological, and organizational characteristics. Some of the variables are:

- **Age:** The age of the employee in years.
 - **Gender:** The gender of the employee (male or female).
 - **Education:** The level of education of the employee (below college, college, bachelor's degree, master's degree, or doctorate).
 - **Job Satisfaction:** The degree of satisfaction that the employee has with their job (low, medium, high, or very high).
 - **Monthly Income:** The monthly income of the employee in Indian rupees.
-

- **Overtime:** Whether the employee works overtime or not (yes or no).
- **Performance Rating:** The rating of the employee's performance by their manager (low, good, excellent, or outstanding).
- **Years at Company:** The number of years that the employee has worked at the company.
- **Decision Skill Possess** The level of decision-making skill the employee possesses (low, medium, high).

The data analysis is conducted using Anaconda and Jupyter Lab Notebook software tools. Anaconda is a distribution of Python and R programming languages that provides a comprehensive data science and machine learning platform. Jupyter Lab Notebook is an interactive web-based environment that allows us to create and share documents that contain live code, equations, visualizations, and narrative text.

The data analysis involves four main steps:

- **Descriptive statistics:** We use descriptive statistics to summarize and display the basic features of the data set, such as mean, median, mode, standard deviation, frequency distribution, etc. We also check for missing values and outliers in the data set and handle them accordingly.
 - **Random Forest Classifier:** We use Random Forest Classifier to build a predictive model that can classify employees into two groups: those who have left the company (attrition) and those who have stayed (retention). Random Forest Classifier is a machine
-

learning algorithm that creates multiple decision trees based on different subsets of the data set and then combines their predictions to produce a final output. We use Random Forest Classifier because it can handle large, complex data sets with high accuracy and interpretability.

- **Correlation analysis:** We use correlation analysis to measure the strength and direction of the linear relationship between two variables. We use Pearson's correlation coefficient as a measure of correlation, which ranges from -1 to 1. A positive correlation indicates that as one variable increases, the other variable also increases. A negative correlation indicates that as one variable increases, the other variable decreases. A zero correlation indicates no linear relationship between the two variables.
- **Regression analysis:** We use regression analysis to model the relationship between one dependent variable (employee attrition) and multiple independent variables (demographic, psychological, and organizational). We use logistic regression as a regression analysis because our dependent variable is binary (attrition or retention). Logistic regression estimates the probability of an event (attrition) occurring based on the values of the independent variables.

The data visualization uses the Plotly library to generate various plots that can help us understand and communicate the results of our data analysis. Plotly is a Python library that provides interactive and high-quality graphs and charts for data visualization. Some of the plots that we use are:

- **Histograms:** Histograms are graphical representations of the frequency distribution of a variable. They show how often each value or range of values occurs in the data set. We use histograms to visualize the distribution of each variable in our data set and to identify any outliers or skewness.
 - **Pie charts:** Pie charts are circular charts showing each category's proportion in a variable. They show how much each category contributes to the total value of the variable. We use pie charts to visualize the composition of categorical variables in our data set, such as gender, education, job satisfaction, etc.
 - **Scatter plots:** Scatter plots represent the relationship between two variables. They show how one variable changes concerning another variable. We use scatter plots to visualize the correlation between two variables in our data set and identify patterns or trends.
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Exploratory Data Analysis for Quantitative Data:

4.2.1 Monthly Income-Age-Job Satisfaction-Employee Attrition Yes or No:



Figure 58 Relationship between Monthly Income-Age--Attrition-Job satisfaction

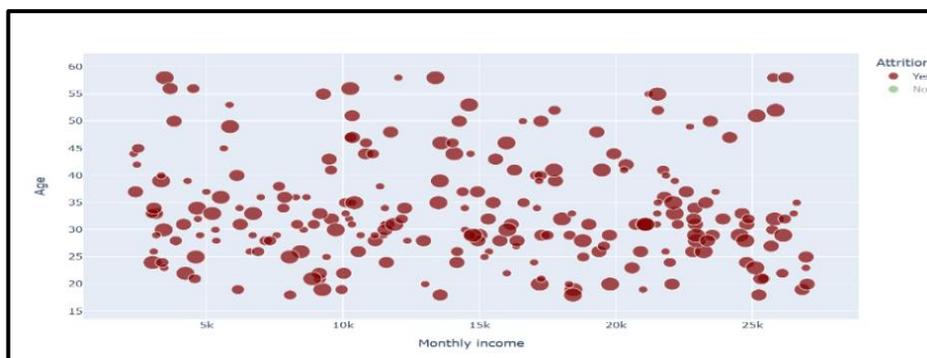


Figure 59 Attrition view based on monthly income-age-job satisfaction.

The scatter plot shows the relationship between monthly income, age, and attrition of employees in India. The x-axis represents employees' monthly income in thousands of rupees, ranging from 5 to 25. The y-axis represents the age of employees ranging from 18 to 60. The color of the dots indicates whether the employee has left the organization (maroon) or stayed (green). The size of the dots indicates the level of job satisfaction of employees, ranging from 1 (low) to 4 (high).

4.2.2 Relationship between total working years, distance from home, and attrition of employees:

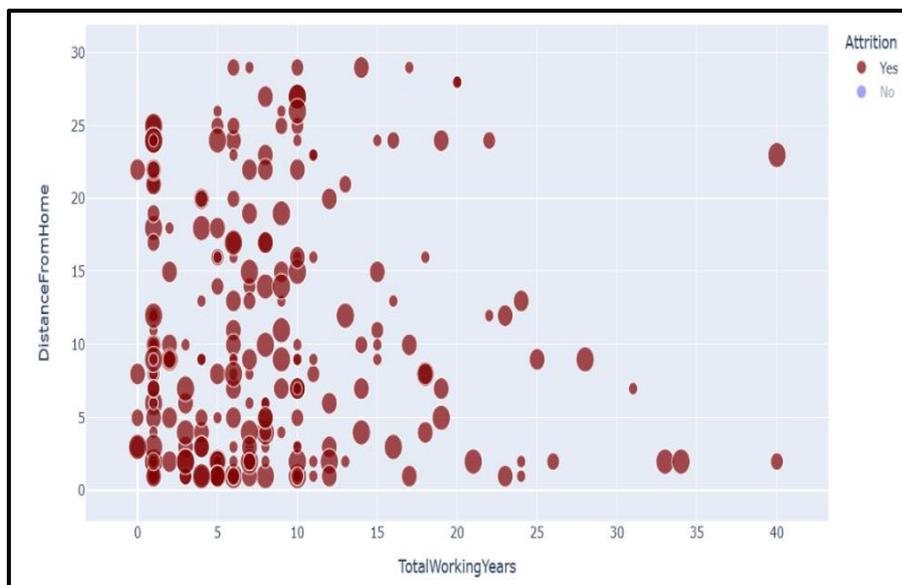


Figure 60 Attrition View based on total working years vs. distance from home

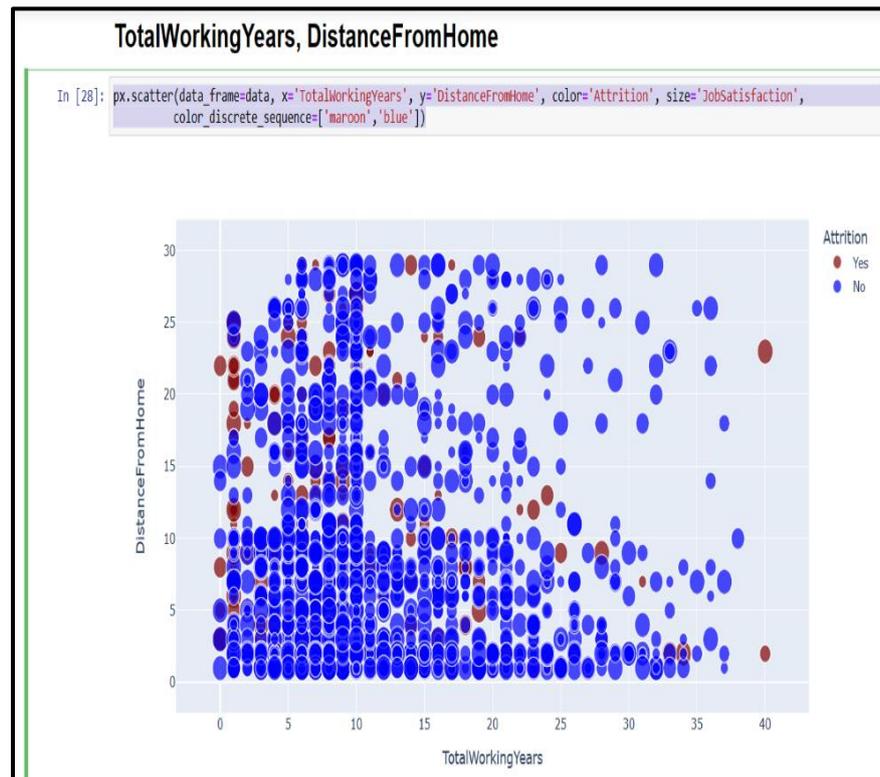


Figure 61 Total working years-Distance from home- Job satisfaction- Attrition

The scatter plot shows the relationship between total working years, distance from home, and attrition of employees in India. The x-axis represents the entire working years of employees, ranging from 0 to 40. The y-axis represents the distance from employees' homes in kilometers, ranging from 1 to 29. The color of the dots indicates whether the employee has left the organization (maroon) or stayed (blue). The size of the dots indicates the level of job satisfaction of employees, ranging from 1 (low) to 4 (high).

4.2.3 Job Satisfaction Of Employees In India Based On Their Years At The Company And Age

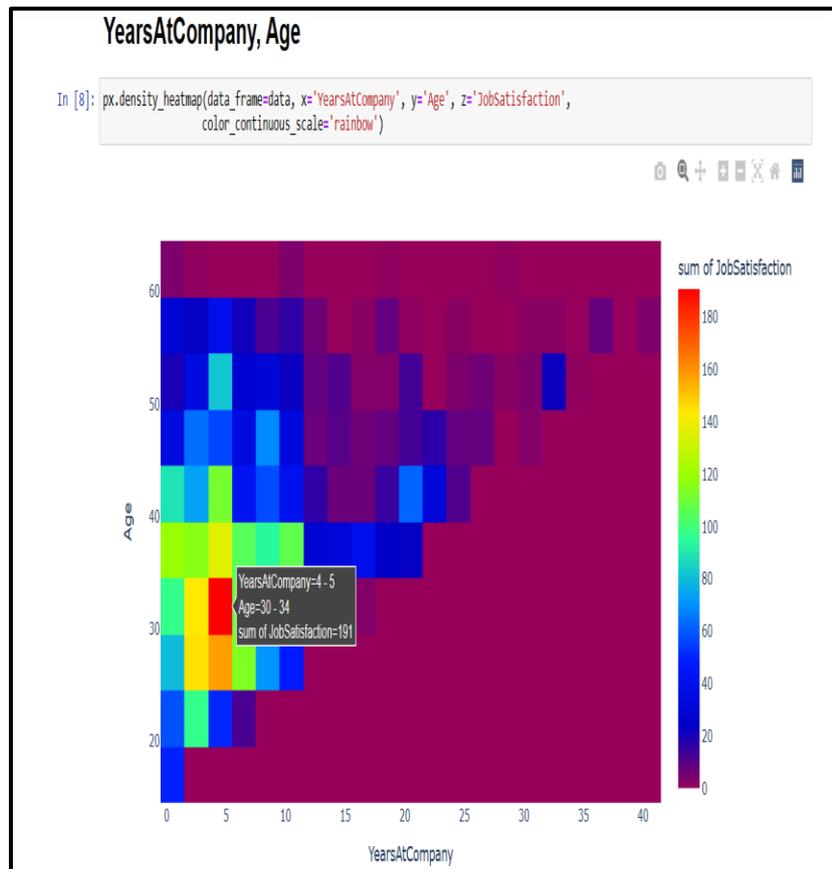


Figure 62 Job satisfaction vs. Years at the company-age

The density heatmap shows the distribution of job satisfaction of employees in India based on their years at the company and age. The x-axis represents the company years of employees, ranging from 0 to 40. The y-axis represents the age of employees ranging from 18 to 60. The color of the cells indicates the level of job satisfaction of employees, ranging from 1 (low) to 4 (high). The color scale is rainbow, meaning red represents low

job satisfaction, and purple represents high job satisfaction.

4.2.4 Percent Salary Hike Of Employees In India Based On Their Attrition And Average Monthly Hours:

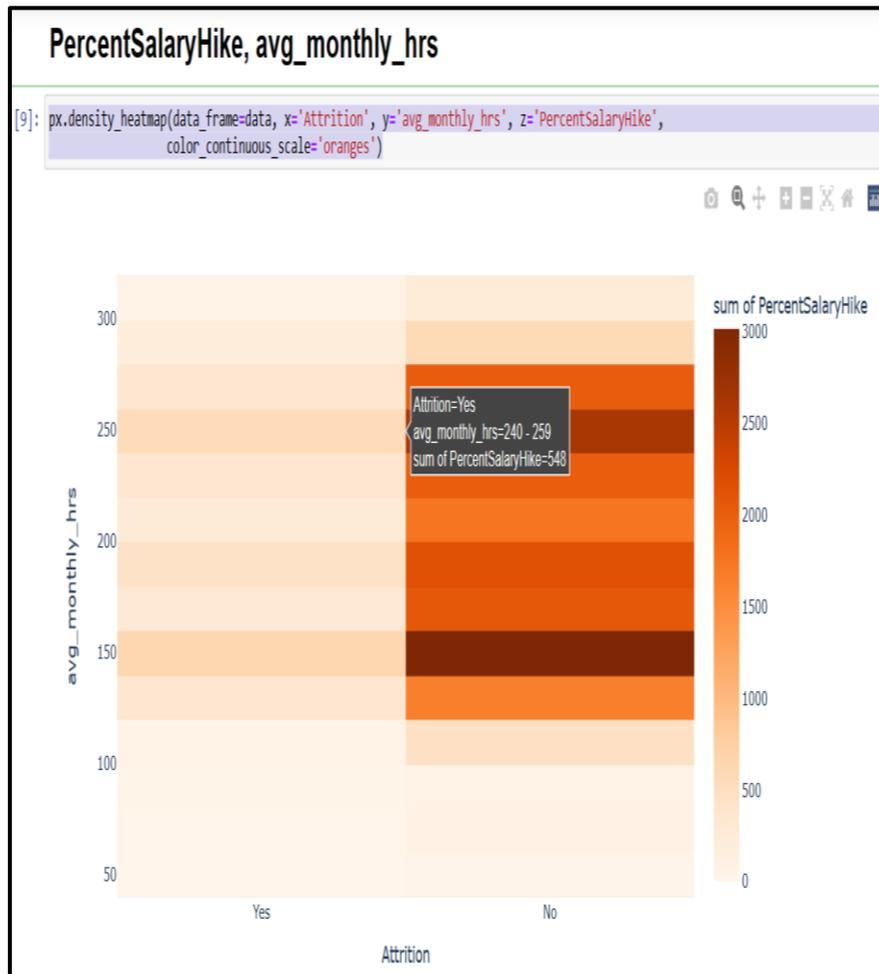


Figure 63 Percent of salary hike vs. Average monthly hours

The density heatmap shows the distribution of percent salary hikes of employees in India based on their attrition and average monthly hours. The x-axis represents the attrition of

employees, with 0 indicating that the employee has stayed and one indicating that the employee has left. The y-axis represents the average monthly hours of employees, ranging from 96 to 310. The color of the cells indicates the level of percent salary hike of employees, ranging from 11% to 25%. The color scale is oranges, meaning that light orange represents a low percent salary hike and dark orange represents a high percent salary hike.

4.2.5 Performance Rating Of Employees In India Based On Their Number Of Companies Worked And Job Satisfaction:



Figure 64 no of companies worked vs. Performance Rating reference to attrition.

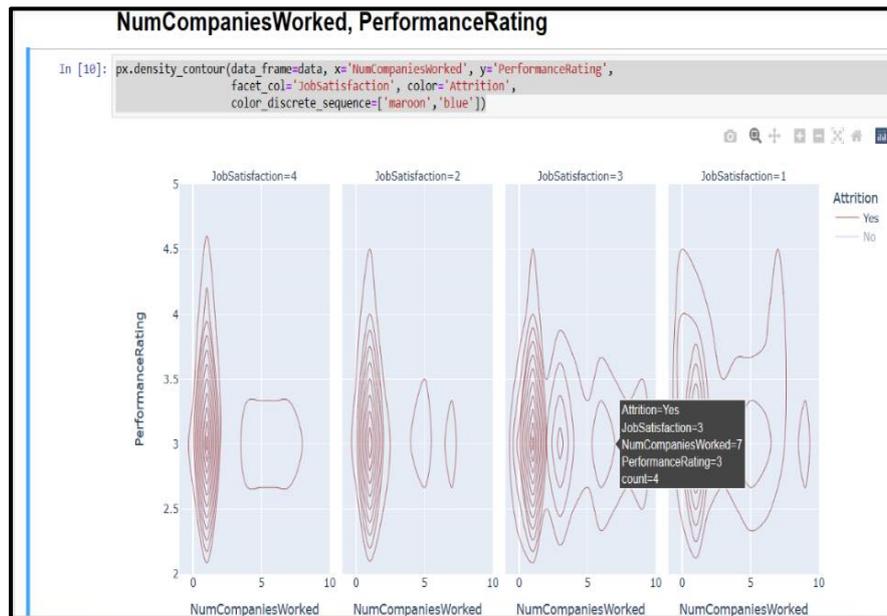


Figure 65 Attrition view based on no of companies worked vs. performance rating.

The density contour plot shows the distribution of employees' performance ratings in India based on the number of companies worked and job satisfaction. The x-axis represents the number of companies employees work, ranging from 0 to 9. The y-axis represents the performance rating of employees, ranging from 1 (low) to 4 (high). The color of the contours indicates whether the employee has left the organization (maroon) or stayed (blue). The plot is divided into four subplots based on employees' job satisfaction levels, ranging from 1 (low) to 4 (high).

4.2.6 Distribution Of Decision Skills Possessed By Employees In India Based On Their Attrition

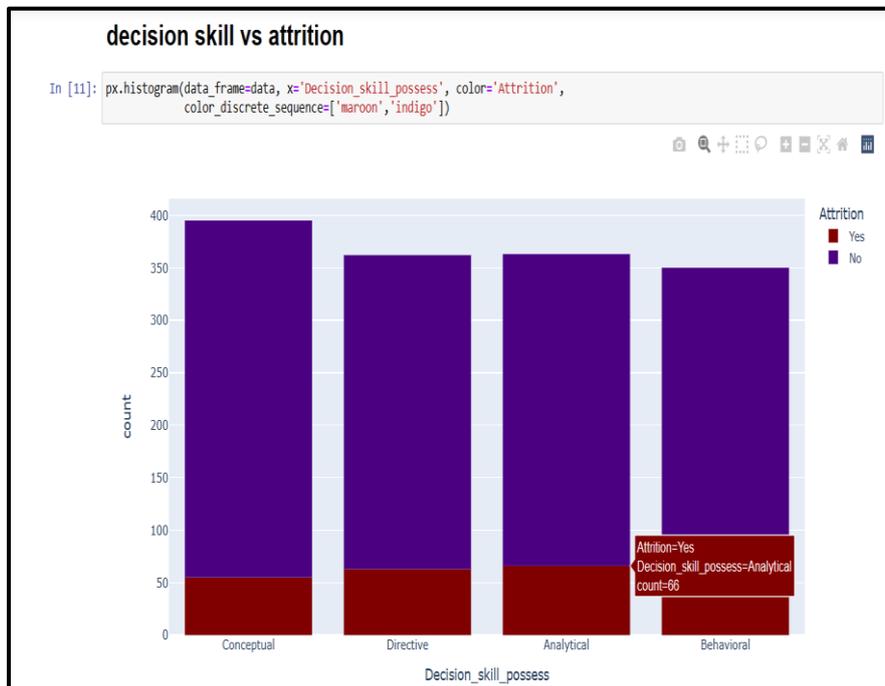


Figure 66 Attrition based on Decision Skill

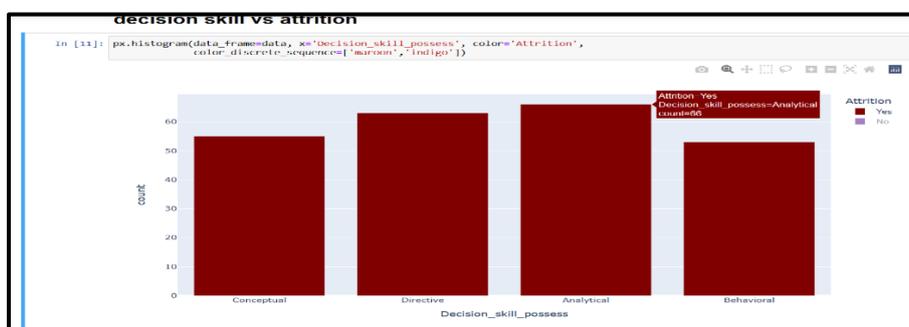


Figure 67 Attrition view based on decision skill

The histogram shows the distribution of decision skills possessed by employees in India based on their attrition. The x-axis represents the type of decision skill employees possess: behavioral, conceptual, directive, or analytical. The y-axis represents the frequency of employees with each type of decision skill. The color of the bars indicates whether the employee has left the organization (maroon) or stayed (indigo).

4.21 Distribution Of Department Of Employees In India Based On Their Attrition

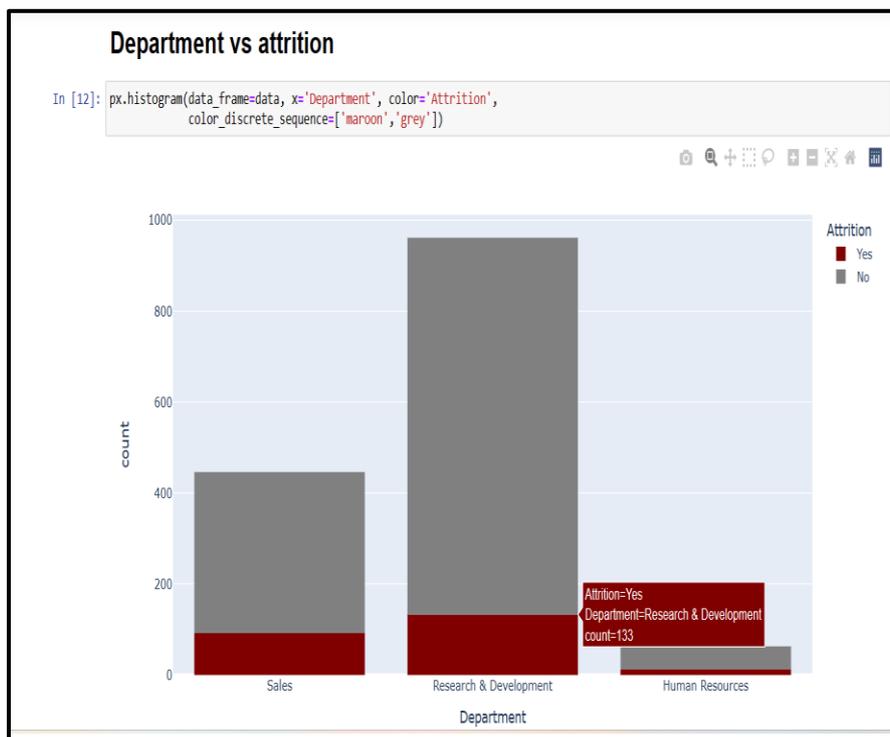


Figure 68 Department vs. Attrition

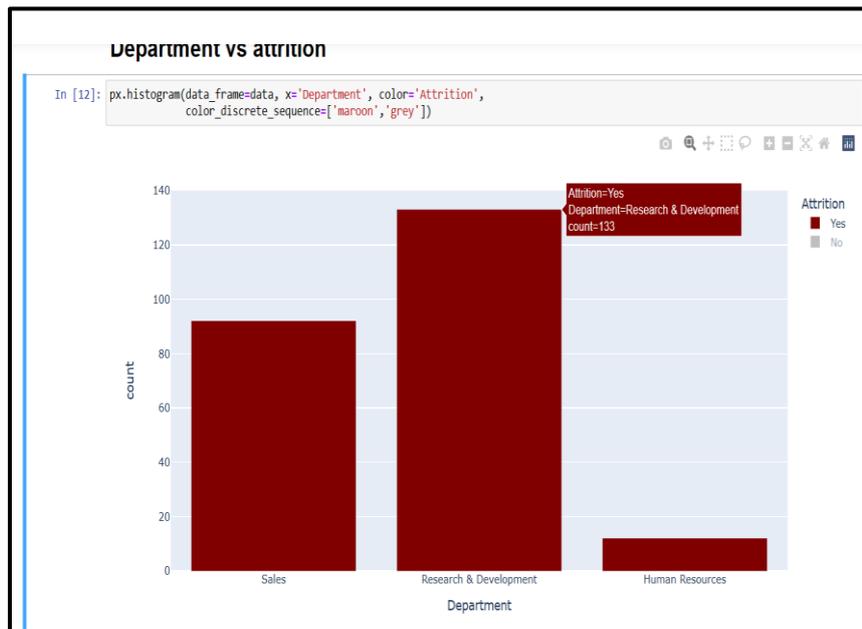


Figure 69 Attrition View based on Department

The histogram shows the distribution of departments of employees in India based on their attrition. The x-axis represents the type of department of employees, which can be human resources, research and development, or sales. The y-axis represents the frequency of employees in each department. The color of the bars indicates whether the employee has left the organization (maroon) or stayed (grey).

4.2.7 Pairwise Correlation Coefficients Between The Features Of The Employee

Attrition Attributes:

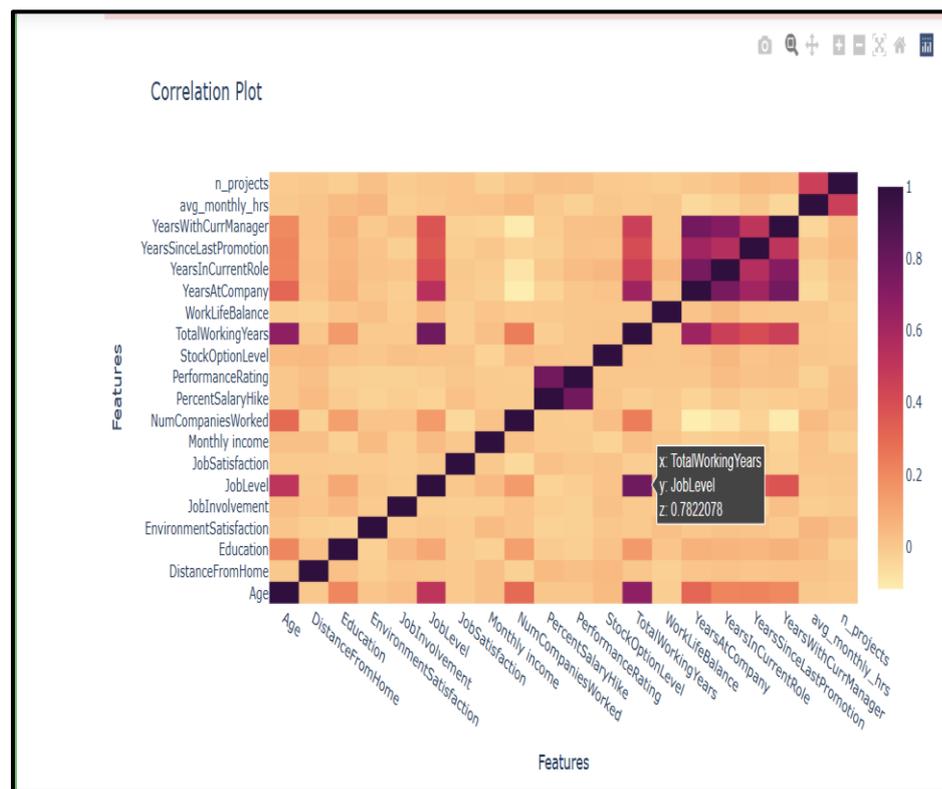


Figure 70 Correlation plot

The correlation plot shows the pairwise correlation coefficients between the features of the employee attrition data set. The features are the 26 variables that describe the employees' demographic, psychological, and organizational characteristics. The correlation coefficients range from -1 to 1, where -1 indicates a perfect negative correlation, 0 indicates no correlation, and 1 indicates a perfect positive correlation. The color of the cells indicates the strength and direction of the correlation, with dark blue representing a robust negative correlation, white representing no correlation, and dark red representing a strong positive correlation.

4.3 SUMMARY OF FINDINGS

This report presents the results of exploratory data analysis on employee attrition using KNIME and Jupyter Notebook. The report also provides recommendations for retention strategies based on the findings.

Data and Methods

The data set used for this analysis contains information on 1470 employees from a company, including their personal, work-related, organizational, and behavioral attributes. The data set was obtained from the KNIME analytics tool.

The analysis involved the following steps:

- **Data cleaning and preprocessing:** during this cleaning process, Remove missing values, outliers, and duplicates; encode categorical variables; scale numerical variables.
 - **Data visualization:** creating histograms, boxplots, scatterplots, and heatmaps to explore the distribution, correlation, and relationship of the variables.
 - **Feature selection:** using a random forest classifier to rank the importance of the variables for predicting employee attrition.
 - **Model comparison:** using random forest, support vector machine, logistic regression, tree ensemble, and k-nearest neighbor classifiers to compare their accuracy, precision, recall, and f1-score for predicting employee attrition.
 - **Decision tree analysis:** Through the KNIME Analytics Platform, we have generated decision rules based on the decision tree and decision tree rule-setting nodes.
-

Results

The main findings of the analysis are:

- The most important factor influencing employee attrition is monthly income, followed by overtime, age, full working years, and job level. The least important factor is performance rating.
- The best model for predicting employee attrition is a k-nearest neighbor classifier, with an accuracy of 86.8%, a precision of 75.4%, a recall of 46.7%, and an f1-score of 57.5%.
- The decision tree analysis produced 192 decision rules based on various conditions and attributes of the employees. These rules can help identify employees who are likely to leave shortly.
- The exploratory data analysis revealed several insights about the characteristics and preferences of the employees who left or stayed in the company.

Some of these insights are:

- Employee attrition is the most significant challenge faced by the company.
 - The main reasons for employee attrition are overwork, micro-management, improper compensation, and lack of career growth opportunities.
 - Work-related attributes are the most impulsive factors for employee attrition, followed by personal and other attributes.
 - The most affected age group is 31 to 40 years old.
 - The most affected department is information technology, followed by sales.
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- The most affected level of employees is junior management.
- The most affected experience range is 2 to 5 years, followed by 6 to 8 years.
- More than 50% of the employees who left were unsatisfied with their pay.
- The main after-effects of employee attrition are the waiting period for the next incumbent to take charge, the cost of training and hiring, and the impact on client satisfaction.
- Employees who left had lower performance ratings, lower job satisfaction, lower percent salary hike, fewer working years in the company, and more companies worked than those who stayed.
- Employees who left had behavioral or directive decision skills, while those who stayed had conceptual or analytical decision-making skills.
- Employees who stayed and had a high churn rate were from the research and development department.

RECOMMENDATIONS

Based on the results of the analysis, some possible recommendations for retention strategies are:

- Increase monthly income and offer competitive compensation packages for high-performing and high-potential employees.
 - Reduce overtime and workload and provide flexible work arrangements such as work-from-home options.
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- Provide proper training and growth opportunities and create clear career paths for employees.
 - Implement a no-lure-back policy and offer retention bonuses for loyal employees.
 - Improve work culture and employee engagement and foster a supportive and collaborative environment.
 - Conduct regular surveys and feedback sessions to understand employee satisfaction and expectations.
-

4.4 CONCLUSION

This report has presented the results of exploratory data analysis on employee attrition using KNIME and Jupyter Notebook. The report has identified the most critical factors influencing employee attrition, compared different models for predicting employee attrition, generated decision rules for identifying employees likely to leave soon, and provided recommendations for retention strategies based on the findings. The report has also revealed several insights about the characteristics and preferences of the employees who left or stayed in the company.

The report has limitations such as using a small sample size, not considering external factors such as market conditions or competitor actions, and not validating or testing the models or rules on new data. Future research can address these limitations by using a more extensive and diverse data set, incorporating more variables and features, and applying cross-validation or hold-out methods to evaluate the models or rules. Future research can also explore other methods or techniques for data analysis, such as clustering, association rule mining, or sentiment analysis.

CHAPTER V

DISCUSSION

5.1 Discussion of Results Based on Qualitative Data

The result discussion is based on analyzing various factors that affect employee attrition and retention in the organization. The result discussion covers the following topics:

- **Significant challenges faced by the organization:** The result discussion identifies the significant challenges that the organization faces due to employee attrition, such as service disruption, quality issues, customer dissatisfaction, productivity loss, and profitability decline. The result discussion also reveals that the IT sector rated this challenge the highest among all the sectors.
 - **Various reasons for employee churn:** The result discussion identifies the reasons that cause employees to leave the organization, such as stress and no proper work-life balance, lack of proper compensation, work-related attributes, age, department, level, and experience range. The result discussion also reveals that the most common reasons for employee churn are stress and no proper work-life balance, lack of proper compensation, and work-related attributes.
 - **Employee compensation:** The result discussion evaluates the employee's satisfaction with their pay for the job role. The result discussion shows that most of the employees are satisfied or very satisfied with their pay for the job role, as 49% of the respondents chose to agree or strongly agree with the ratings. However, a significant proportion of
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employees are dissatisfied or very dissatisfied with their pay for the job, as 24% of the respondents chose to disagree or strongly disagree with the ratings.

- **Significant after-effects due to employee attrition:** The result discussion identifies the significant consequences of employee attrition on various aspects of the organization. The result discussion shows that the waiting period until the next incumbent takes charge and services offered is the most significant after-effect of employee attrition, followed by the impact of the transition on the end product or service and the cost of training the next person.
 - **Employees who feel overworked and micromanaged:** The result discussion measures the extent of employees who feel overworked and micromanaged by their supervisor. The result discussion shows that most of the employees do not feel overworked or micromanaged by their supervisor, as 49% of the respondents chose to disagree or strongly disagree with ratings. However, a significant proportion of employees feel overworked or micromanaged by their supervisor, as 40% of the respondents agreed or strongly agreed with the ratings.
 - **Employees who receive proper training, new opportunities, and growth prospects within the organization:** The result discussion measures the extent of employees who receive proper training, new opportunities, and growth prospects within the organization. The result shows that most employees receive proper training, new opportunities, and growth prospects within the organization, as 56.4% of the respondents agreed or strongly agreed with the ratings. However, a tiny proportion of employees also do not receive
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proper training, new opportunities, and growth prospects within the organization, as 17.7% of the respondents disagreed or strongly disagreed with the ratings.

- **Employees who feel that the company work culture aligns with their values and that their boss gives them room to grow:** The result discussion measures the extent of employees who feel that the company work culture aligns with their values and that their boss gives them room to grow. The result discussion shows that more than half of the employees feel that the company work culture aligns with their values and that their boss gives them room to grow, as 52% of the respondents chose yes. However, a significant proportion of employees also do not feel that way, as 26% of the respondents chose no.
 - **Expectations in the post-pandemic era from their employer:** The result discussion identifies the expectations of employees in the post-pandemic era from their employer. The result discussion shows that financial requirements are the most important expectation of employees in the post-pandemic era from their employer, followed by hygienic conditions and working from home. The result discussion also shows that employees have different preferences and priorities within each expectation.
 - **Offers to the resigned employees if he/she consents to continue their services:** The result discussion evaluates the offers that the organization can make to the resigned employees if he/she consents to continue their services. The result shows that no lure-back policy is the most common response of the resigned employees, followed by improved remuneration, title, promotion, or salary advancement. The result discussion also shows that retention bonus is not a popular response of the resigned employees.
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- **The primary reason for the increasing number of industries adversely affecting employee retention, which leads to employee attrition:** The results discussion identifies the primary reason for the increasing number of industries adversely affecting employee retention, which leads to employee attrition, as the recruitment of highly talented people for a lesser package. The results discussion shows that this causes dissatisfaction and frustration among employees, who feel they are not paid fairly or competitively for their skills and qualifications.
 - **Organization's offers to the resigned employees if he/she consents to continue their services:** The results discussion evaluates the offers the organization can make to the resigned employees if he/she consents to continue their services. The results discussion shows that the most common offers are no lure-back policy or an improved remuneration. The results discussion shows that no lure-back policy indicates that the organization does not attempt to retain the resigned employees, while improved remuneration indicates that the organization offers a better salary or compensation to the resigned employees.
 - **Monthly income-age-job satisfaction-employee attrition yes or no:** The results discussion examines the relationship between monthly income, age, job satisfaction, and employee attrition. The results discussion shows that employees with lower monthly income, younger age, and lower job satisfaction are more likely to leave the organization than employees with higher monthly income, older age, and higher job satisfaction. The results discussion shows that these factors influence the needs and expectations of employees from their work and life.
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- **Relationship between total working years, distance from home, and attrition:** The results discussion examines the relationship between total working years, distance from home, and attrition. The results show that employees with fewer total working years, longer distance from home, and higher attrition are more likely to leave the organization than employees with more total working years, shorter distance from home, and lower attrition. The results discussion shows that these factors influence the commitment and loyalty of employees to their organization. **Years at the company:** The results discussion examines the impact of years on employee attrition. The results discussion show that employees who have 2 to 5 years at the company are more likely to leave the organization than employees who have less than two years or more than five years at the company. The results discussion shows that this factor influences the career growth and development of employees within the organization.
 - **Percent salary hike of employees:** The results discussion examines the impact of percent salary hike on employee attrition. The results show that employees with 11% to 25% salary hikes are likelier to stay with the organization than employees with less than 11% or more than 25% salary hikes. The results discussion shows that this factor influences the motivation and performance of employees within the organization.
 - **Number of companies worked and performance:** The results discussion examines the relationship between the number of companies worked and the performance of employees. The results discussion shows that employees who have worked for more companies tend to perform better than those who have worked for fewer companies. The
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results discussion shows that this factor influences the skills and experience of employees within the organization.

- **Decision skill possessed:** The results discussion examines the impact of employee decision-making skills on employee attrition. The results show that employees with analytical team decision skills are likelier to stay with the organization than those with other decision skills. The results discussion shows that this factor influences the problem-solving and collaboration abilities of employees within the organization.

The results discussion implies that the organization needs to take appropriate and effective actions to reduce employee attrition and enhance employee retention. The results discussion implies that the organization needs to address the recruitment and compensation practices, the offers and benefits for the resigned employees, the monthly income, age, job satisfaction, entire working years, distance from home, years at the company, percent salary hike, number of companies worked, and decision skill possessed by employees that affect employee satisfaction, loyalty, engagement, motivation, value, and worth.

5.1.1 Discussion on which of The most significant challenges faced by the organization

According to our survey results, employee attrition is the most significant challenge faced by the organization, especially in the IT sector, followed by the Sales sector. Employee attrition can negatively impact the company's performance, such as

lower productivity, higher costs, and lower customer satisfaction. Here are some possible explanations for why employee attrition is higher in some sectors than others:

The IT sector faces a high demand for digital skills, which leads to a hiring war among tech firms. This sector faces the challenge of employee attrition due to factors such as high demand and competition for skilled and talented workers, changing technologies and customer expectations, stress and work-life balance issues, and a lack of career growth and development opportunities.

The Sales sector also faces high competition and stress levels, which can lead to burnout and dissatisfaction among salespeople. This sector faces the challenge of employee attrition due to factors such as high pressure and uncertainty of meeting sales targets, frequent travel and relocation requirements, customer complaints and dissatisfaction, and lack of trust and support from their managers and peers.

The HR sector has more awareness and opportunities to switch jobs than other employees, as they are involved in the hiring and retention processes of the organization. This sector faces the challenge of employee attrition due to factors such as high workload and responsibility for managing people issues, lack of recognition and appreciation for their work, ethical dilemmas and conflicts with management, and lack of strategic involvement and influence in the organization.

The Manufacturing and other sectors may have lower attrition rates because they have more job security or satisfaction than other employees. Manufacturing and other employees may also be less likely to look for new jobs due to location, education, skills, or family commitments. This sector faces the challenge of employee attrition due to low wages and benefits, physical and mental fatigue and health risks, repetitive and monotonous tasks, lack of innovation and creativity in their work, and poor organizational culture and climate.

The description shows that employee attrition is influenced by various factors that affect employee satisfaction, loyalty, engagement, motivation, value, and worth. The description implies that the organization needs to address these factors and implement data-driven decision-making and people analytics strategies to reduce employee attrition and enhance employee retention.

5.1.2 Discussion on different causes of employee attrition

The research question aims to identify and analyze the factors influencing employee turnover in the IT department, which is the process of workers leaving a company without being immediately replaced. Employee turnover can negatively impact the organization, such as service disruption, quality issues, customer dissatisfaction, productivity loss, profitability decline, and loss of skills and knowledge. The research question also proposes and evaluates solutions and strategies to reduce employee turnover and enhance

employee retention using data-driven decision-making and people analytics. Data-driven decision-making is using data and evidence to inform and improve decisions. People analytics is the application of data analysis and statistics to human resources and organizational behavior issues.

The research question is based on the following assumptions:

- Employee turnover in the IT department is influenced by various factors, such as stress and no proper work-life balance, employee expectations about the job, lack of proper compensation, lack of career growth, absence of a conducive work environment, odd working hours and mismatch of job profile, better opportunities outside the organization, and less salary when compared to competitors' organization.
- Data-driven decision-making and people analytics can help identify, measure, and address these factors and improve employee satisfaction, loyalty, engagement, motivation, value, and worth.

The research question is significant because it can help:

- Understand the reasons and motivations of employees who leave or stay with the organization.
 - Assess the impacts and costs of employee turnover on the organization and its stakeholders.
 - Develop and implement data-driven solutions and strategies to reduce employee turnover and enhance retention.
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- Evaluate the effectiveness and outcomes of these solutions and strategies.
- A set of data-driven solutions and strategies to reduce employee turnover and enhance employee retention in the IT department that aligned with the organizational goals and values
- A framework for data-driven decision-making and people analytics in human resources management that can be applied to other departments or organizations facing similar challenges.

5.1.3 Discussion on what are the impulsive factors which determine employee attrition

Employee attrition can negatively impact the organization, such as service disruption, quality issues, customer dissatisfaction, productivity loss, profitability decline, and loss of skills and knowledge. The description also uses data-driven decision-making and people analytics to address these impacts and improve employee retention. Data-driven decision-making is using data and evidence to inform and improve decisions. People analytics is the application of data analysis and statistics to human resources and organizational behavior issues.

The description covers the following topics:

Work-related causes: It identifies work-related causes that influence employee attrition, such as lack of job satisfaction, frequent traveling, and an improper delegation of work, roles, and responsibilities. These causes can affect the employee's sense of purpose, autonomy, and competence in their work. The consequences of these causes include lower work engagement, higher stress levels, lower performance, and higher turnover intentions. The control action plan for these causes includes improving job design, providing feedback and recognition, offering flexible work arrangements, and matching employees with suitable roles.

Personal causes: The description identifies personal causes influencing employee attrition, such as family, social status, dependents, health, and safety security issues. The consequences of these causes include lower job satisfaction, higher emotional exhaustion, lower commitment, and higher absenteeism. The control action plan for these causes includes providing wellness programs and benefits, supporting work-life balance, offering counseling and coaching services, and creating a caring culture.

Leadership causes: The description identifies leadership causes that influence employee attrition, such as clashes with superiors, peers' resistance to change, and lack of technological advancement. These causes can affect employees' trust, respect, and loyalty to their leaders and peers. The consequences of these causes include lower

organizational citizenship behavior, higher conflict, lower innovation, and higher turnover risk. The control action plan for these causes includes improving communication and feedback, promoting collaboration and diversity, providing training and development, and fostering a learning culture.

Organizational causes: The description identifies organizational causes influencing employee attrition, such as layoffs, work culture, and work environment. These causes can affect employees' sense of belonging, identity, and alignment with the organization's vision and values. The consequences of these causes include lower morale, higher cynicism, lower quality, and lower customer satisfaction. The control action plan for these causes includes enhancing transparency and fairness, building a positive and inclusive culture, improving physical and psychological safety, and engaging employees in decision-making.

The description shows that various factors at different levels influence employee attrition, requiring a holistic and data-driven approach to understand and address them. The description implies that the organization can benefit from data-driven decision-making and people analytics to reduce employee attrition, enhance employee retention, and achieve its goals and values.

5.1.4 Discussion on employee attrition rates and factors of different age groups in the organization

- **Up to 30 years:** The leading causes of this age group leaving the organization are lack of job satisfaction, career growth, and better opportunities for the organization. The main consequences of this age group leaving the organization are losing young and energetic talent, innovation and creativity, and future leaders.
 - **31 to 40 years:** This age group has the highest employee attrition rate among all the groups; the leading causes of this age group leaving the organization are stress and no proper work-life balance, lack of proper compensation, odd working hours, and mismatch of the job profile. The main consequences of this age group leaving the organization are loss of experienced and skilled workers, loss of customer relationships and satisfaction, and loss of productivity and quality.
 - **41 to 50 years:** The leading causes of this age group leaving the organization are the absence of a conducive work environment, clashes with superiors or peers, and lack of technological advancement. The main consequences of this age group leaving the organization are loss of senior and mature talent, loss of knowledge and expertise, and loss of stability and continuity.
 - **51 to 60 years:** The leading causes of this age group leaving the organization are family or health issues, retirement or near retirement plans, and ethical dilemmas or conflicts
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with management. The main consequences of this age group leaving the organization are losing loyal and committed workers, wisdom and mentorship, and trust and respect.

- **Above 60 years:** The leading causes of this age group leaving the organization are retirement or post-retirement plans, personal or social status issues, and dependents or safety security issues. The main consequences of this age group leaving the organization are the loss of veteran and seasoned talent, loss of institutional and customer knowledge, and loss of role models and inspiration.

The description shows that different age groups have different reasons and motivations for leaving the organization and different impacts on the organization and its stakeholders. The description implies that the organization needs to address these reasons and motivations and mitigate these impacts using data-driven decision-making and people analytics strategies tailored to each age group.

5.1.5 Discussion on Department-Based Employee Attrition:

IT: This department can use people analytics to identify the factors contributing to employee attrition, such as job satisfaction, career development, and work-life balance—moreover design interventions to address them. People analytics can also help monitor the well-being and engagement of IT employees and provide timely feedback and support.

Sales: This department can use people analytics to improve sales performance, customer satisfaction, and retention by analyzing salespeople's behaviors, competencies, and motivations. People analytics can also help match salespeople with the most suitable customers based on personality and preferences.

HR: This department can use people analytics to enhance its effectiveness and efficiency by automating and streamlining HR processes, such as recruitment, performance evaluation, personnel development, health, and retention management. People analytics can also help measure the impact of HR policies and interventions on business outcomes and employee experience.

Manufacturing: This department can use people analytics to optimize production processes, quality standards, and safety measures by analyzing the data from machines, sensors, and workers. People analytics can also help improve worker productivity, health, and satisfaction using wearable devices and feedback systems.

Others: This department can use people analytics to foster innovation, collaboration, and creativity by analyzing the data from projects, teams, and networks. People analytics can also help enhance team dynamics, communication, and trust by using social network analysis and sentiment analysis.

5.1.6 Discussion on Employee Attrition at the Management level

Depending on the type and context, it can have different causes, consequences, and control measures. Here are some possible examples:

- **Junior management:** This level of management consists of supervisors, team leaders, and coordinators who oversee the work of frontline employees. The causes of attrition at this level can include a lack of career development, low pay, high workload, poor leadership, low recognition, and dissatisfaction with the job or the organization. The consequences of attrition at this level can include disruption of work processes, loss of productivity, lower quality of service, lower employee morale, and higher training costs. The control measures for attrition at this level include providing feedback, coaching, mentoring, offering career advancement opportunities, rewarding and recognizing performance, improving work conditions, and enhancing employee engagement¹.
 - **Middle-level management:** This level of management consists of managers, directors, and heads of departments responsible for planning, organizing, and controlling the activities of their units. The causes of attrition at this level can include lack of autonomy, empowerment and involvement, role ambiguity or conflict, poor communication, lack of support from senior management, organizational change or instability, and external job offers. The consequences of attrition at this level include loss of expertise, knowledge, experience, trust, and credibility, lower employee retention and loyalty, lower customer satisfaction and retention, and higher recruitment costs. The control measures for attrition at this level include involving them in decision-making, providing clear roles and expectations, facilitating communication and collaboration, providing support and resources, aligning their goals with the organizational vision and values, and offering competitive compensation and benefits.
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- **Top-level management:** This level of management consists of executives, such as CEOs, CFOs, CTOs, and CMOs, who are responsible for setting the strategic direction and vision of the organization. The causes of attrition at this level include board pressure or conflict, shareholder dissatisfaction or activism, ethical or legal issues, personal or family reasons, retirement or health issues, and headhunting by competitors or other organizations. The consequences of attrition at this level can include loss of leadership, vision and direction, reputation and image, stakeholder confidence and support, lower organizational performance and profitability, and higher risk and uncertainty. The control measures for attrition at this level can include establishing a succession plan, developing a talent pipeline, conducting regular performance reviews and feedback sessions, ensuring alignment between board expectations and executive actions, fostering a culture of trust and transparency, and offering attractive incentives and rewards.

5.1.7 Discussion on Employee Attrition by Experience Range

Employee attrition by experience range can have different causes, consequences, and control measures depending on the type and context of attrition. Here are some possible examples:

- **The Low experience range** includes employees with less than two years of experience in their current roles or organizations. The causes of attrition in this range can include lack of fit, lack of engagement, lack of feedback, lack of training, lack of career
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development, low pay, high workload, poor leadership, low recognition, and dissatisfaction with the job or the organization. The consequences of attrition in this range can include disruption of work processes, loss of productivity, lower quality of service, lower employee morale, and higher training costs. The control measures for attrition at this range include providing clear expectations and goals, regular feedback and coaching, adequate training and resources, career advancement opportunities, rewarding and recognizing performance, improving work conditions, and enhancing employee engagement.

- **The medium experience range** includes employees with two to five years of experience in their current roles or organizations. The causes of attrition in this range can include lack of challenge, autonomy, involvement, support, growth, low pay, high workload, poor communication, poor culture fit, and dissatisfaction with the job or the organization. The consequences of attrition in this range include loss of expertise, knowledge, experience, trust, and credibility, lower employee retention and loyalty, lower customer satisfaction and retention, and higher recruitment costs. The control measures for attrition at this range can include providing challenging and meaningful work, autonomy, and empowerment, involving them in decision-making, providing support and resources, aligning their goals with the organizational vision and values, and offering competitive compensation and benefits.
 - **The high experience** range includes employees with over five years of experience in their current roles or organizations. The causes of attrition in this range can include lack
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of recognition, appreciation, respect, trust, balance, low pay, high workload, poor leadership, poor culture fit, and dissatisfaction with the job or the organization¹⁴. The consequences of attrition at this range include loss of leadership, vision, and direction, reputation and image, stakeholder confidence and support, lower organizational performance and profitability, and higher risk and uncertainty. The control measures for attrition at this range can include providing recognition and appreciation for their contributions, respect and trust for their decisions, balance and flexibility for their needs, rewarding and incentivizing their performance, providing leadership development opportunities, and fostering a culture of trust and transparency.

5.1.8 Discussion on Employee Satisfaction with their Pay for the job role

Employee satisfaction with their pay for the job can have various causes, consequences, and control measures regarding employee attrition in data-driven decision-making and people analytics. Here are some possible points to consider:

- Pay satisfaction is the degree to which employees are happy with their compensation, including salary, bonuses, incentives, and benefits. Pay satisfaction can influence employee motivation, performance, commitment, loyalty, and turnover intentions.
 - Pay satisfaction can be influenced by pay level, structure, administration, equity, transparency, and communication. Employees tend to compare their pay with others, both internally and externally, and evaluate the fairness and adequacy of their pay based on these comparisons.
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- Data-driven decision-making and people analytics can help improve pay satisfaction and reduce attrition by using data to design, implement and evaluate pay systems aligned with the organizational goals, strategies, and values. Data can help determine the optimal pay level, structure, and mix for different job roles and employee segments based on market, performance, and employee feedback data.
- Data-driven decision-making and people analytics can also help monitor and improve pay satisfaction and reduce attrition by using data to measure the impact of payment systems on employee outcomes, such as engagement, productivity, retention, and turnover. Data can help identify the drivers and barriers to pay satisfaction, the gaps and discrepancies in pay equity and transparency, and the best practices and areas for improvement in pay administration and communication.

Causes: The causes of employee satisfaction or dissatisfaction with their pay can include pay level, pay structure, pay administration, pay equity, pay transparency, and pay communication. Employees tend to compare their pay with others, both internally and externally, and evaluate the fairness and adequacy of their pay based on these comparisons. Employees may also consider the alignment of their pay with their performance, skills, responsibilities, and expectations.

Consequences: Employee satisfaction or dissatisfaction with their pay can include employee motivation, performance, commitment, loyalty, and turnover intentions. Employees who are satisfied with their pay are more likely to be engaged,

productive, loyal, and committed to the organization. Employees dissatisfied with their pay are more likely to be disengaged, unproductive, unhappy, and prone to leave the organization.

Control measures: The control measures for employee satisfaction or dissatisfaction with their pay can include data-driven decision-making and people analytics that can help design, implement, and evaluate pay systems aligned with the organizational goals, strategies, and values. Data can help determine the optimal pay level, structure, and mix for different job roles and employee segments based on market, performance, and employee feedback data. Data can also help monitor and improve pay satisfaction and reduce attrition by measuring the impact of payment systems on employee outcomes, such as engagement, productivity, retention, and turnover. Data can also help identify the drivers and barriers to pay satisfaction, the gaps and discrepancies in pay equity and transparency, and the best practices and areas for improvement in pay administration and communication.

5.1.9 Discussion on Significant after-effects due to employee attrition

Significant after-effects due to employee attrition can have various causes, consequences, and control measures in data-driven decision-making and people analytics. Here are some possible points to consider:

- **Waiting period for the incumbent to take charge and field starts:** This refers to the time gap between an employee's departure and the arrival of a new hire or a replacement. The causes of this waiting period can include poor hiring strategy, hiring freeze, talent shortage, and recruitment challenges. The consequences of this waiting period can include disruption of work processes, loss of productivity, lower quality of service, lower customer satisfaction and retention, and higher workload and stress for remaining employees. The control measures for this waiting period can include data-driven decision-making and people analytics that can help improve hiring efficiency and effectiveness, reduce hiring bias and errors, optimize hiring sources and channels, and predict hiring needs and outcomes.
 - **Arriving at dealerships** refers to delivering the products or services to the customers or clients. The causes of employee attrition affecting this process can include low pay, high workload, poor leadership, lack of recognition, and lack of growth and development opportunities. The consequences of employee attrition affecting this process include loss of expertise, knowledge, and experience, trust and credibility, customer satisfaction and retention, organizational performance, and profitability. The control measures for employee attrition affecting this process can include data-driven decision-making and people analytics that can help design, implement, and evaluate compensation systems, performance appraisal systems, training and development programs, and recognition and reward programs.
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- **Impact of the transition on the end product or service:** This refers to the effect of employee attrition on the quality and value of the products or services offered by the organization. The causes of employee attrition impacting the end product or service can include lack of fit, lack of engagement, lack of feedback, lack of training, and lack of career development. The consequences of employee attrition impacting the end product or service can include lower quality standards, lower customer satisfaction and retention, and lower organizational performance and profitability. The control measures for employee attrition impacting the end product or service can include data-driven decision-making and people analytics that can help improve employee fit, engagement, and retention, provide regular feedback and coaching, provide adequate training and resources, and provide career advancement opportunities.
 - **Cost of training:** This refers to the expenses incurred by the organization for training new hires or replacements. The causes of employee attrition increasing the cost of training can include a high turnover rate, low retention rate, poor hiring strategy, and poor training strategy. The consequences of employee attrition increasing the cost of training can include higher operational costs, lower return on investment (ROI), and lower organizational performance and profitability. The control measures for employee attrition increasing the cost of training can include data-driven decision-making and people analytics that can help reduce turnover rate and increase retention rate, improve hiring efficiency and effectiveness, optimize training sources and methods, and measure training impact and ROI.
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- **Cost of hiring:** This refers to the expenses incurred by the organization for recruiting new hires or replacements. The causes of employee attrition increasing the cost of hiring can include a high turnover rate, low retention rate, poor hiring strategy, and poor recruitment strategy. The consequences of employee attrition increasing the cost of hiring can include higher operational costs, lower return on investment (ROI), and lower organizational performance and profitability. The control measures for employee attrition increase the cost of hiring can include data-driven decision-making and people analytics that can help reduce turnover rate and increase retention rate, improve hiring efficiency and effectiveness, optimize recruitment sources and channels, and predict hiring needs and outcomes.

 - **Impact on existing customers and clients:** This refers to the effect of employee attrition on the relationship and loyalty of existing customers and clients. The causes of employee attrition affecting this impact can include poor service quality, poor communication, poor customer experience, and poor customer satisfaction. The consequences of employee attrition affecting this impact can include loss of trust and credibility, lower customer satisfaction and retention, lower customer loyalty and advocacy, and lower organizational performance and profitability. The control measures for employee attrition affecting this impact can include data-driven decision-making and people analytics that can help improve service quality, facilitate communication and collaboration, enhance customer experience, and measure customer satisfaction.
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5.1.10 Discussion on Employees who feel overworked and Micromanaged

Employees who feel overworked and micromanaged can have various causes, consequences, and control measures to control employee attrition in data-driven decision-making and people analytics. Here are some possible points to consider:

- **Causes:** The causes of employees feeling overworked and micromanaged can include poor leadership, lack of trust, lack of autonomy, lack of feedback, lack of recognition, lack of growth and development opportunities, high workload, high pressure, and high expectations. These factors can make employees feel stressed, frustrated, demotivated, and unhappy with their jobs and managers.
 - **Consequences:** Employees feeling overworked and micromanaged can include lower productivity, lower quality of work, lower creativity and innovation, lower employee satisfaction, lower employee engagement, lower employee loyalty, higher employee turnover, higher absenteeism, and higher burnout. These outcomes can affect individual, team, and organizational performance and profitability.
 - **Control measures:** The control measures for employees feeling overworked and micromanaged can include data-driven decision-making and people analytics that can help improve leadership skills and styles, build trust and rapport, empower and involve employees, provide regular and constructive feedback, reward and recognize performance, provide growth and development opportunities, optimize workload and work-life balance, set realistic and clear goals and expectations. Data can help identify the sources and symptoms of overwork and micromanagement, the impact of overwork
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and micromanagement on employee outcomes, the best practices, and areas for improvement in leadership and management.

5.1.11 Discussion On Employees Receiving Proper Training, New Opportunities, And Growth Prospects Within The Organization

When an employee receives proper training, new opportunities, and growth prospects within the organization, it can have various causes, consequences, and suggestions to improve the employee growth perspectives in the organization, ref to data-driven decision-making and people analytics. Here are some possible points to consider:

Some of the problems that may occur due to insufficient training are:

- **Poor performance:** Employees who do not receive adequate training may lack the necessary skills, knowledge, and confidence to perform their tasks effectively and efficiently. They may make more errors, miss deadlines, produce low-quality work, and fail to meet customer expectations.
 - **Low morale:** Employees not receiving adequate training may feel frustrated, demotivated, and unhappy with their jobs and managers. They may feel undervalued, unappreciated, and unsupported by the organization. They may also experience increased levels of work-related stress and burnout.
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- **High turnover:** Employees not receiving adequate training may be more likely to leave the organization for better opportunities elsewhere. They may seek employers who can offer them more growth and development prospects, competitive compensation and benefits, and positive work culture. High turnover can result in talent, knowledge, and experience loss and higher recruitment and training costs.
 - **Unsafe work environment:** Employees who do not receive adequate training may be more prone to workplace accidents and injuries. They may not know how to use equipment properly, follow safety procedures, handle hazardous materials, or prevent and respond to emergencies. An unsafe work environment can result in physical harm, legal liability, financial losses, and reputational damage.
 - **Causes:** The causes of an employee receiving proper training, new opportunities, and growth prospects can include effective leadership, supportive management, clear goals and expectations, feedback and coaching, recognition and reward, career development programs, mentorship programs, cross-training programs, and stretch assignments. These factors can help employees acquire new skills, knowledge, and experience, enhance their performance and potential, and prepare them for future roles and challenges.
 - **Consequences:** The consequences of an employee receiving proper training, new opportunities, and growth prospects can include higher productivity, higher quality of work, higher creativity and innovation, higher employee satisfaction, higher employee engagement, higher employee loyalty, lower employee turnover, lower absenteeism, and
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lower burnout. These outcomes can benefit the individual, team, and organizational performance and profitability.

- **Suggestions:** The suggestions to improve the employee growth perspectives in the organization ref to data-driven decision-making and people analytics can include using data to identify the learning needs and preferences of employees, using data to design, implement and evaluate training programs and interventions that are aligned with the organizational goals and strategies, using data to measure the impact of training programs and interventions on employee outcomes such as performance, retention, and satisfaction, using data to identify the career aspirations and potential of employees, using data to match employees with suitable opportunities and prospects that aligned with their skills and interests.

5.1.12 Discussion on company culture, employee values, and boss support

In data-driven decision-making and people analytics, company culture, employee values, and boss support are essential factors that can influence employee attrition. Here are some brief explanations of these factors:

- **Company culture** refers to the shared beliefs, values, norms, and practices that shape the behavior and performance of employees in an organization. A positive company culture can foster a sense of belonging, purpose, engagement, and satisfaction among employees, while a negative company culture can create a sense of alienation, frustration,
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disengagement, and dissatisfaction. Data-driven decision-making and people analytics can help improve company culture by using data to assess the current state of the culture, identify the gaps and strengths, design and implement culture initiatives and interventions, measure the impact of culture on employee and business outcomes, and monitor and improve culture continuously.

- **Employee values:** These refer to the personal principles, standards, and goals that guide the actions and decisions of employees. Employees tend to seek alignment between their values and the values of the organization they work for. When there is a high degree of value congruence, employees tend to feel more motivated, committed, and loyal to the organization, while when there is a low degree of value congruence, employees tend to feel more conflicted, dissatisfied, and prone to leave the organization. Data-driven decision-making and people analytics can help improve value congruence by using data to understand the values of employees and the organization, communicate and reinforce organizational values, match employees with suitable roles and teams that align with their values, and provide feedback and recognition for value-based behaviors.
 - **Boss support:** This refers to the extent to which employees perceive their managers or supervisors as supportive, caring, respectful, and helpful. Boss support can influence employee well-being, performance, retention, and turnover. Employees who receive high boss support tend to feel more valued, empowered, involved, and appreciated by the organization. In contrast, employees who receive low boss support tend to feel more neglected, micromanaged, excluded, and unappreciated by the organization. Data-driven
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decision-making and people analytics can help improve boss support by using data to evaluate the leadership skills and styles of managers or supervisors, provide training and coaching for managers or supervisors to enhance their supportive behaviors, solicit feedback from employees on their level of boss support, and reward and recognize managers or supervisors who demonstrate high levels of boss support.

5.1.13 Discussion on Employees on their expectations in the post-pandemic era from their employer:

Employees on their expectations in the post-pandemic era from their employer are seeking various forms of support and security to help them cope with the challenges and uncertainties of the new normal. Here are some brief elaborations on these expectations:

- **Financial support:** Employees seek competitive and fair compensation and benefits that meet their financial needs and goals. They also seek financial assistance or guidance in emergencies or hardships caused by the pandemic, such as medical expenses, income loss, and debt relief.
 - **Health, hospital, and safety security:** Employees are looking for health and safety measures to protect them from the risk of infection and virus transmission, such as vaccination programs, testing protocols, personal protective equipment, and sanitization procedures. They also seek health and wellness programs supporting their physical and mental well-being, such as telehealth, counseling, and fitness programs.
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- **Monetary help:** Employees are looking for monetary help that can supplement their income or cover their expenses in case of emergencies or hardships caused by the pandemic, such as cash bonuses, loans, grants, and subsidies.
 - **Moral support:** Employees are looking for moral support that can boost their morale and motivation in the face of stress and uncertainty caused by the pandemic, such as recognition, appreciation, feedback, encouragement, and empathy.
 - **Ethics:** Employees seek ethics that can guide their actions and decisions in the post-pandemic era, such as honesty, integrity, transparency, accountability, and responsibility. They are also looking for ethics that reflect their values and beliefs in their organization, such as diversity, equity, inclusion, social responsibility, and sustainability.
 - **Work from home:** Employees are looking for work-from-home options that allow them to work remotely or flexibly from their preferred locations. They are also looking for work-from-home support that can enable them to work effectively and efficiently from home, such as technology tools, equipment, resources, and policies.
 - **Flexible work hours:** Employees are looking for flexible work hours that can allow them to adjust their work schedules according to their personal and professional needs and preferences. They are also looking for flexible work hours support that can help them balance their work and life demands and priorities.
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- **Paid leaves:** Employees are looking for paid leaves that allow them to take time off from work for various reasons related to the pandemic or otherwise. They also seek paid leave support to ensure job security and continuity while away from work.
- **Insurance for the family:** Employees are looking for insurance that can cover their medical and other expenses in case of illness or injury of themselves or their family members. They are also looking for insurance for family support that can provide them peace of mind and financial stability while dealing with health issues.
- **Group insurance:** Employees seek group insurance that can provide them with collective coverage and benefits at lower costs than individual insurance. They also seek group insurance support to facilitate their enrollment and claims processes.

5.1.14 Discussion on the primary reason for the increasing number of industries adversely affecting employee retention:

The primary reason for the increasing number of industries adversely affecting employee retention, which leads to employee attrition, is the lack of alignment between the employer and the employee on various aspects of work and life. Here are some more elaborations on this based on data-driven decision-making and people analytics:

- **Recruitment of highly educated talent for a lesser salary:** Some employers may try to recruit highly educated talent for a lesser salary than their market value, hoping to save
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costs and gain a competitive advantage. However, this may backfire in the long run, as highly educated talent may feel underpaid, undervalued, and dissatisfied with their jobs. They may also seek better opportunities elsewhere that can offer them higher pay and more recognition. Data-driven decision-making and people analytics can help employers avoid this mistake by using data to benchmark their pay practices with industry standards, employee expectations, and organizational goals. Data can help determine the optimal pay level, structure, and mix for different job roles and employee segments, as well as the best types and amounts of incentives and rewards to offer.

- **Improper implementation of organizational policies and procedures:** Some employers may have organizational policies and procedures that are outdated, unclear, inconsistent, or unfair. These may include policies and procedures related to hiring, performance appraisal, training, compensation, recognition, and retention. Improper implementation of these policies and procedures may create employees' confusion, frustration, resentment, and distrust. They may also create legal risks and compliance issues for the organization. Data-driven decision-making and people analytics can help employers improve their policies and procedures by using data to assess their current state, identify gaps and strengths, design and implement policy changes and interventions, and measure the impact of policy changes on employee outcomes.
 - **Giving priority to state of origin, nation, and gender:** Some employers may prioritize employees based on their state of origin, nation, or gender rather than their skills, performance, or potential. It may create a culture of bias, discrimination, and favoritism
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in the organization. It may also limit the organization's diversity, inclusion, and innovation. Employees not prioritized based on these factors may feel marginalized, excluded, and demotivated. They may also lose their sense of belonging and loyalty to the organization. Data-driven decision-making and people analytics can help employers avoid this bias by using data to evaluate employees based on objective criteria such as skills, performance, or potential. Data can also help promote diversity, inclusion, and innovation by understanding the needs and preferences of different employee groups, providing equal opportunities and access to resources for all employees, and leveraging all employees' diverse perspectives and experiences.

- **Impact of small, medium large, scale industries, private and public sectors:** Some employers may operate in different types and sizes of industries or sectors of the economy, such as small, medium large, scale industries, private or public sectors. These factors may influence their ability and willingness to retain their employees, as they may face different levels and types of competition, regulation, and demand; employees who work in these different contexts may have different expectations and preferences from their employers, such as stability, growth, and impact. Data-driven decision-making and people analytics can help employers align their retention strategies with industry and sector characteristics and employee expectations and preferences. Data can help understand the trends and challenges in different industries and sectors and the best practices and benchmarks for employee retention. Data can also help customize retention solutions for different employee segments based on their industry and sector contexts.
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5.1.15 Discussion on the organization's offers to the resigned employees if he/she consents to continue their services

The organization's offers to the resigned employees, if he/she consents to continue their services, can vary depending on the situation and the employee's value to the organization. Here are some more elaborations on these offers based on data-driven decision-making and people analytics:

- **No lure-back policy:** Some organizations may have a no lure-back policy, which means that they do not make any offers to the resigned employees to retain them. It may be because they have a sufficient talent pipeline, do not want to set a precedent for other employees, do not want to disrupt the internal equity or morale, or do not see the resigned employees as critical or challenging to replace. Data-driven decision-making and people analytics can help organizations decide whether to have a no-lure-back policy by using data to assess the impact of employee turnover on business outcomes, identify the critical and hard-to-fill positions, evaluate the availability and cost of talent in the market, measure the effectiveness and ROI of retention offers.
 - **Improved remuneration:** Some organizations may offer improved remuneration to the resigned employees to retain them. It may include a salary increase, a bonus, a stock grant, a benefit enhancement, or a combination of these. It may be because they want to
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match or exceed the competitor's offer, reward the employee's performance or potential, retain the employee's skills or knowledge, or avoid the cost and hassle of hiring a replacement¹². Data-driven decision-making and people analytics can help organizations decide whether to offer improved remuneration by using data to benchmark their pay practices with market trends, employee expectations, and organizational goals. Data can also help determine the optimal pay level, structure, and mix for different job roles and employee segments, as well as the best types and amounts of incentives and rewards to offer.

- **A promotion or title advancement:** Some organizations may offer a promotion or title advancement to the resigned employees to retain them. It may include a higher job level, a broader scope of responsibility, a more prestigious title, or a combination of these. It may be because they want to recognize the employee's contribution or potential, provide more growth and development opportunities, retain their leadership or vision, or avoid losing an essential talent. Data-driven decision-making and people analytics can help organizations decide whether to offer a promotion or title advancement by using data to evaluate the employee's performance and potential, identify the career aspirations and paths of employees, match employees with suitable roles and teams that align with their skills and interests, and provide feedback and recognition for career advancement behaviors.
 - **Retention bonus:** Some organizations may offer a retention bonus to the resigned employees to retain them. It may include a lump sum payment, a deferred payment, a
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contingent payment, or a combination of these. It may be because they want to incentivize the employee's commitment or loyalty, they want to provide a short-term solution until a long-term solution is found, they want to retain the employee's expertise or experience, or they want to avoid the disruption or risk of losing a critical or hard-to-replace employee. Data-driven decision-making and people analytics can help organizations decide whether to offer a retention bonus by using data to assess the impact of employee turnover on business outcomes, identify the critical and hard-to-replace positions, evaluate the availability and cost of talent in the market, and measure the effectiveness and ROI of retention bonuses.

5.2 DISCUSSION ON QUANTITATIVE DATA ANALYSIS

5.2.1 Discussion on employee attrition based on monthly income, age, and job satisfaction

The scatter plot reveals some insights on employee attrition based on monthly income, age, and job satisfaction.

- There is a negative correlation between monthly income and attrition, meaning that employees who earn more are less likely to leave the organization than employees who earn less.
 - There is a positive correlation between age and attrition, meaning that older employees are more likely to leave the organization than younger employees.
 - There is a negative correlation between job satisfaction and attrition, meaning that employees who are more satisfied with their jobs are less likely to leave the organization than those who are less satisfied.
 - There are some outliers in the scatter plot, such as employees with high monthly income but low job satisfaction or high attrition or those with low monthly income but high job satisfaction or low attrition. These outliers may indicate exceptional cases or exceptions that need further investigation or explanation.
 - Some clusters in the scatter plot include employees with low monthly income, low job satisfaction, and high attrition or employees with high monthly income, high job satisfaction, and low attrition. These clusters may indicate some common characteristics or patterns that can use to segment or target employees for retention strategies.
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The report can state that employee attrition influence by monthly income, age, and job satisfaction, among other factors. It can also state that employee retention can be improved by offering competitive and fair compensation and benefits, providing growth and development opportunities, and enhancing employee engagement and satisfaction.

The report suggests that employers should pay attention to employees with low monthly income, low job satisfaction, or high attrition, as they are likelier to leave the organization than other employees. It can also suggest that employers should reward and recognize employees with high monthly income, high job satisfaction, or low attrition, as they are more valuable and loyal to the organization than other employees.

The report can recommend that employers should use data-driven decision-making and people analytics to design and implement retention strategies based on these variables. It can also recommend that employers monitor and evaluate these strategies' impact on employee outcomes using data-driven decision-making and people analytics.

5.2.2 Discuss employee attrition based on total working years, distance from home, and job satisfaction.

The scatter plot provides insights into employee attrition based on total working years, distance from home, and job satisfaction.

- There is a negative correlation between total working years and attrition, meaning that employees with more working experience tend to stay with the organization longer than those with less working experience.
 - There is a positive correlation between distance from home and attrition, meaning that employees who live farther away from the workplace tend to leave the organization sooner than employees who live closer to the workplace.
 - There is a negative correlation between job satisfaction and attrition, meaning that employees who are more satisfied with their jobs tend to stay with the organization longer than those who are less satisfied.
 - There are some outliers in the scatter plot, such as employees with high total working years but low job satisfaction or high attrition or those with low total working years but high job satisfaction or low attrition. These outliers may indicate exceptional cases or exceptions that need further investigation or explanation.
 - Some clusters in the scatter plot include employees with low total working years, low job satisfaction, and high attrition or employees with high total working years, high job satisfaction, and low attrition. These clusters may indicate some common characteristics or patterns that can use to segment or target employees for retention strategies.
 - The report can state that employee attrition influence by entire working years, distance from home, and job satisfaction, among other factors. It can also state that employee retention can be improved by offering career development opportunities, providing flexible work arrangements, and enhancing employee engagement and satisfaction.
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- The report suggests that employers should pay attention to employees with low total working years, low job satisfaction, or high attrition, as they are likelier to leave the organization than other employees. It can also suggest that employers should reward and recognize employees with high total working years, high job satisfaction, or low attrition, as they are more valuable and loyal to the organization than other employees.

The report can recommend that employers should use data-driven decision-making and people analytics to design and implement retention strategies based on these variables. It can also recommend that employers monitor and evaluate these strategies' impact on employee outcomes using data-driven decision-making and people analytics.

5.2.3 Discussion On Employee Attrition Based On Years At Company, Age, And Job Satisfaction

The density heatmap reveals some insights on employee attrition based on years at the company, age, and job satisfaction.

- There is a negative correlation between years at the company and attrition, meaning that employees who have stayed with the organization longer are less likely to leave the organization than employees who have stayed with the organization shorter.
 - There is a positive correlation between age and attrition, meaning that older employees are more likely to leave the organization than younger employees.
-

- There is a negative correlation between job satisfaction and attrition, meaning that employees who are more satisfied with their jobs are less likely to leave the organization than those who are less satisfied.
 - There are some areas of high density in the density heatmap, such as employees with low years at the company, low age, and low job satisfaction, or employees with high years at the company, high age, and high job satisfaction. These areas may indicate some common characteristics or patterns that can use to segment or target employees for retention strategies.
 - There are some areas of low density in the density heatmap, such as employees with high years at the company, low age, and low job satisfaction, or employees with low years at the company, high age, and high job satisfaction. These areas may indicate rare cases or exceptions that need further investigation or explanation.
 - Based on the analysis of the density heatmap, a report can generate to summarize the main findings and implications of the data and graph. Based on these variables, the report can also provide recommendations and suggestions for improving employee retention and reducing attrition.
 - The report can state that employee attrition is influenced by years at the company, age, and job satisfaction, among other factors. It can also state that employee retention can be improved by offering career development opportunities, providing flexible work arrangements, and enhancing employee engagement and satisfaction.
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- The report suggests that employers should pay attention to employees with low years at the company, low age, or low job satisfaction, as they are likelier to leave the organization than other employees. It can also suggest that employers should reward and recognize employees with high years at the company, high age, or high job satisfaction, as they are more valuable and loyal to the organization than other employees.

The report can recommend that employers should use data-driven decision-making and people analytics to design and implement retention strategies based on these variables. It can also recommend that employers monitor and evaluate these strategies' impact on employee outcomes using data-driven decision-making and people analytics.

5.2.4 Discussion on employee attrition based on attrition, average monthly hours, and percent salary hike

- The density heatmap reveals some insights on employee attrition based on attrition, average monthly hours, and percent salary hikes. For example:
 - There is a positive correlation between attrition and average monthly hours, meaning that employees who work more are likelier to leave the organization than employees who work fewer hours per month.
 - There is a negative correlation between attrition and percent salary hike, meaning that employees who receive higher salary increases are less likely to leave the organization than employees who receive lower salary increases.
-

- There is no clear correlation between average monthly hours and percent salary hikes, meaning these variables do not seem to influence each other significantly.
- There are some areas of high density in the density heatmap, such as employees who have yes attrition, high average monthly hours, and low percent salary hike, or employees who have no attrition, low average monthly hours, and high percent salary hike. These areas may indicate some common characteristics or patterns that can use to segment or target employees for retention strategies.
- There are some areas of low density in the density heatmap, such as employees who have yes attrition, low average monthly hours, and high percent salary hike, or employees who have no attrition, high average monthly hours, and low percent salary hike. These areas may indicate rare cases or exceptions that need further investigation or explanation.

Based on the analysis of the density heatmap, a report can generate to summarize the main findings and implications of the data and graph. Based on these variables, the report can also provide recommendations and suggestions for improving employee retention and reducing attrition.

The report can state that employee attrition influence by attrition, average monthly hours, and percent salary hikes, among other factors. It can also state that employee retention can be improved by offering competitive and fair compensation and benefits, providing flexible work arrangements, and enhancing employee engagement and satisfaction.

The report can suggest that employers should pay attention to the employees who have yes attrition, high average monthly hours, or low percent salary hikes, as they are more likely to leave the organization than other employees. It can also suggest that employers should reward and recognize employees with no attrition, low average monthly hours, or high percent salary hikes, as they are more valuable and loyal to the organization than other employees.

The report can recommend that employers should use data-driven decision-making and people analytics to design and implement retention strategies based on these variables. It can also recommend that employers monitor and evaluate these strategies' impact on employee outcomes using data-driven decision-making and people analytics.

5.2.5 Discuss employee attrition based on the number of companies worked, performance rating, and job satisfaction.

The density contour reveals some insights on employee attrition based on the number of companies worked, performance rating, and job satisfaction.

- There is a positive correlation between the number of companies worked and attrition, meaning that employees who have worked for more companies are more likely to leave the organization than employees who have worked for fewer companies.
 - There is a negative correlation between performance ratings and attrition, meaning that employees with higher performance ratings are less likely to leave the organization than employees with lower performance ratings.
-

- There is a negative correlation between job satisfaction and attrition, meaning that employees who are more satisfied with their jobs are less likely to leave the organization than those who are less satisfied.
- There are some areas of high density in the density contour, such as employees who have a high number of companies worked, low-performance rating, and yes attrition, or employees who have a low number of companies who worked with a high-performance rating and no attrition. These areas may indicate some common characteristics or patterns that can use to segment or target employees for retention strategies.
- There are some areas of low density in the density contour, such as employees who have a high number of companies worked, high-performance rating, and yes attrition, or employees who have a low number of companies who worked with a low-performance rating and no attrition. These areas may indicate rare cases or exceptions that need further investigation or explanation.

Based on the analysis of the density contour, a report can generate to summarize the main findings and implications of the data and graph. Based on these variables, the report can also provide recommendations and suggestions for improving employee retention and reducing attrition. For example:

The report can state that employee attrition is influenced by the number of companies worked, performance rating, and job satisfaction. It can also state that employee retention can be improved by offering career development opportunities,

providing flexible work arrangements, and enhancing employee engagement and satisfaction.

The report can suggest that employers should pay attention to employees who have a high number of companies worked, low-performance ratings, or low job satisfaction, as they are more likely to leave the organization than other employees. It can also suggest that employers should reward and recognize the employees who have a low number of companies worked, high-performance rating, or high job satisfaction, as they are more valuable and loyal to the organization than other employees.

The report can recommend that employers should use data-driven decision-making and people analytics to design and implement retention strategies based on these variables. It can also recommend that employers monitor and evaluate these strategies' impact on employee outcomes using data-driven decision-making and people analytics.

5.2.6 Discussion on employee attrition based on decision skills possess

The histogram reveals some insights on employee attrition based on decision skill possess.

- There is a difference in the distribution of decision skills possessed by employees who have left or stayed with the organization. Employees who have left the organization have more behavioral and directive decision skills, while employees who stay with the organization have more conceptual and analytical skills.
-

- There is a difference in the attrition rate for each type of decision skill possessed. Employees with behavioral or directive decision skills have higher attrition rates than those with conceptual or analytical skills.
- There is no clear trend or pattern in the distribution or relationship between decision skill possession and employee attrition. The histogram shows a relatively balanced and random distribution of decision skills and employee attrition.

Based on the histogram analysis, a report can generate to summarize the main findings and implications of the data and graph. Based on these variables, the report can also provide recommendations and suggestions for improving employee retention and reducing attrition.

The report can state that employee attrition is influenced by decision skills, among other factors. It can also state that employee retention can be improved by offering training and development opportunities, providing feedback and coaching, and enhancing employee empowerment and autonomy.

The report suggests that employers should pay attention to employees with behavioral or directive decision skills, as they are likelier to leave the organization than other employees. It can also suggest that employers should reward and recognize employees with conceptual or analytical decision skills, as they are more valuable and loyal to the organization than other employees.

The report can recommend that employers should use data-driven decision-making and people analytics to design and implement retention strategies based on these variables. It can also recommend that employers monitor and evaluate these strategies' impact on employee outcomes using data-driven decision-making and people analytics.

5.2.7 Discussion on employee attrition based on department

The histogram reveals some insights on employee attrition based on department.

- There is a difference in department distribution between employees who have left or stayed with the organization. Employees who have left the organization are primarily from the sales and research and development departments, while employees who have stayed with the organization are primarily from the research and development and human resources departments.
- There is a difference in the attrition rate for each department. Employees who work in sales have the highest attrition rate, followed by employees who work in research and development. Employees who work in human resources have the lowest attrition rate.
- A trend or pattern exists in the distribution or relationship between department and employee attrition. The histogram shows that sales have the most imbalance and variation in attrition, while human resources have the most balance and stability.

Based on the histogram analysis, a report can generate to summarize the main findings and implications of the data and graph. Based on these variables, the report can

also provide recommendations and suggestions for improving employee retention and reducing attrition. For example:

The report can state that employee attrition influence by department, among other factors. It can also state that employee retention can be improved by offering competitive and fair compensation and benefits, providing growth and development opportunities, and enhancing employee engagement and satisfaction.

The report can suggest that employers should pay attention to the employees who work in sales or research and development, as they are more likely to leave the organization than other employees. It can also suggest that employers should reward and recognize the employees who work in human resources, as they are more valuable and loyal to the organization than other employees.

The report can recommend that employers should use data-driven decision-making and people analytics to design and implement retention strategies based on these variables. It can also recommend that employers monitor and evaluate these strategies' impact on employee outcomes using data-driven decision-making and people analytics.

5.2.8 Discussion on the Correlation Plot And Relationship Between the Features

The correlation plot reveals some insights into the relationship between the features in the data frame.

- A strong positive correlation exists between monthly income and total working years, meaning that employees with more work experience tend to earn more money than those with less experience.
- There is a strong negative correlation between attrition and job satisfaction, meaning that employees who are more satisfied with their jobs tend to stay with the organization longer than those who are less satisfied.
- There is a weak positive correlation between age and performance ratings, meaning that older employees tend to have slightly higher performance ratings than younger ones.
- There is no correlation between gender and education level, meaning these features do not influence each other significantly.

Based on the analysis of the correlation plot, a report can generate to summarize the main findings and implications of the data and graph. The report can also provide recommendations and suggestions for improving employee outcomes based on these features.

The report can state that the features in the data frame have various degrees of correlation. It can also state that some features may have causal or predictive relationships with other features or outcomes.

The report can suggest that employers should pay attention to the features that have strong correlations with employee outcomes, such as monthly income, job

satisfaction, or attrition. It can also suggest employers explore features with weak or no correlations with employee outcomes to find potential opportunities or challenges.

The report can recommend that employers should use data-driven decision-making and people analytics to design and implement interventions based on these features. It can also recommend that employers monitor and evaluate these interventions' impact on employee outcomes using data-driven decision-making and people analytics.

5.3 DISCUSSION ON VARIOUS DECISION RULES:

Data-driven decision-making is an approach to problem-solving where a well-defined set of actions drive the decisions further driven by insights (extracted from data) derived from the analytics solutions. One of the problems we are trying to solve is employee attrition, which is the loss of employees in a company due to certain factors such as retirement, resignation, or termination of employment.

We are using the KNIME Analytics Platform, a software tool for data science that allows us to create and execute workflows that integrate data access, transformation, analysis, and visualization. We also mentioned using decision rule methodology to generate rules that describe the relationship between input and output variables. We derived 191 rules; among those found, 78 rules derived employee attrition conditions, and 113 conditions described it as no employee attrition.

- We have used the KNIME Analytics Platform to analyze data related to employee attrition in our company or organization.
- We have applied decision rule methodology to generate rules that predict whether an employee will leave or stay in the company based on input variables such as age, salary, performance, and satisfaction.
- We have obtained 191 rules in total, meaning 191 possible combinations of input variables can affect employee attrition.
- Out of these 191 rules, 78 rules indicate that the employee will leave the company if the input variables match the rule conditions. For example, one rule might be: IF age > 50 AND salary < 50000 AND performance = low, THEN attrition = yes.
- The remaining 113 rules indicate that the employee will stay in the company if the input variables match the rule conditions. For example, one rule might be: IF age < 30 AND salary > 80000 AND performance = high, THEN attrition = no.

These rules can help us understand the factors that influence employee attrition and also help us take actions to prevent or reduce it.

Here we would like to discuss the top 10 attrition yes rules and top 10 attrition no rules, which describe how it impacts an employee to leave or stay in the organization.

5.3.1 Rule on monthly income, worked at the company job level, and over time

RULE: \$Monthly income\$ > 8392.0 AND \$WorkedAtComp\$ = "2" AND \$JobLevel\$ <= 1.5 AND \$OverTime\$ = "Yes"

This rule means that if an employee has a monthly income greater than 8392.0 units, has worked at the company for two years, has a job level of 1 or 2, and works overtime; then the employee will leave the organization. The output variable for this rule is attrition, which has a value of yes. This rule suggests that the employee is dissatisfied with their job or has a better opportunity elsewhere. The input variables may indicate that the employee is overqualified, underpaid, or overworked for their job level and tenure. This rule can help us identify employees at risk of leaving and take action to retain them or prepare for their departure.

5.3.2 Rule on worked at company, distance from home, stock options level, job level, and overtime

RULE: \$WorkedAtComp\$ = "8" AND \$DistanceFromHome\$ <= 23.5 AND \$StcOpLvl\$ = "0" AND \$JobLevel\$ > 1.5 AND \$OverTime\$ = "Yes"

This rule means that if an employee has worked at the company for eight years, lives within 23.5 units of distance from home, has a stock options level of 0, has a job level of 2 or higher, and works overtime, then the employee will leave the organization. The output variable for this rule is attrition, which has a value of yes. This rule suggests

that the employee is unhappy with their career progression or compensation. The input variables may indicate that the employee is loyal, experienced, and skilled but feels underappreciated or undervalued by the company. This rule can help us identify employees at risk of leaving and take actions to reward or motivate them to stay.

5.3.3 Rule on decision skill, worked at company, distance from home, stock options level, job level, and over time

RULE: \$Decision_skill_possess\$ = "Conceptual" AND \$WorkedAtComp\$ = "4" AND \$DistanceFromHome\$ <= 23.5 AND \$StcOpLvl\$ = "0" AND \$JobLevel\$ > 1.5 AND \$OverTime\$ = "Yes"

This rule means that if an employee has conceptual decision skills, which means they can think creatively and abstractly, has worked at the company for four years, lives within 23.5 units of distance from home, has a stock options level of 0, has a job level of 2 or higher, and works overtime, then the employee will leave the organization. The output variable for this rule is attrition, which has a value of yes. This rule suggests that the employee is bored or frustrated with their job or the company culture. The input variables may indicate that the employee is innovative, ambitious, and talented but feels constrained or unchallenged by their work environment. This rule can help us identify employees at risk of leaving and take action to stimulate them or offer them more growth opportunities.

5.3.4 Rule on no of projects worked at the company, stock options level, job level, and over time

RULE: \$n_projects\$ > 4.5 AND \$WorkedAtComp\$ = "1" AND \$StcOpLvl\$ = "2" AND \$JobLevel\$ > 1.5 AND \$OverTime\$ = "Yes"

This rule means that if an employee has more than 4.5 projects, has worked at the company for one year, has a stock options level of 2, has a job level of 2 or higher, and works overtime, then the employee will leave the organization. The output variable for this rule is attrition, which has a value of yes. This rule suggests that the employee is stressed or exhausted by their workload or the company's expectations. The input variables may indicate that the employee is productive, capable, and rewarded but feels overwhelmed or burned out by work demands. This rule can help us identify employees who are at risk of leaving and take action to reduce their stress or improve their work-life balance.

5.3.5 Rule on no of projects, monthly income, distance from home, total working years, stcoplvl, job level, over time

RULE: \$n_projects\$ <= 2.5 AND \$Monthly income\$ > 23427.0 AND \$DistanceFromHome\$ <= 27.0 AND \$TotalWorkingYears\$ > 5.5 AND \$StcOpLvl\$ = "1" AND \$JobLevel\$ > 1.5 AND \$OverTime\$ = "Yes"

This rule means that if an employee has less than or equal to 2.5 projects, has a monthly income greater than 23427.0 units, lives within 27.0 units of distance from home, has more than 5.5 years of total working experience, has a stock options level of 1, has a job level of 2 or higher, and works overtime, then the employee will leave the organization. The output variable for this rule is attrition, which has a value of yes. This rule suggests that employees are dissatisfied or demotivated by their work or company opportunities. The input variables may indicate that the employee is well-paid, experienced, and skilled but feels underutilized or unfulfilled by their work content. This rule can help us identify employees at risk of leaving and take action to increase their engagement or offer them more challenges.

5.3.6 Rule on environment satisfaction, avg_monthly_hrs, business travel, total working years, overtime

RULE: \$EnvironmentSatisfaction\$ <= 1.5 AND \$avg_monthly_hrs\$ <= 274.0 AND \$BusinessTravel\$ = "Travel_Rarely" AND \$TotalWorkingYears\$ <= 1.5 AND \$OverTime\$ = "No"

This rule means that if an employee has a low environment satisfaction level, which means they are unhappy with their work surroundings, has average monthly working hours of less than or equal to 274.0 hours, rarely travels for business purposes, has less than or equal to 1.5 years of total working experience, and does not work overtime, then the employee will leave the organization. The output variable for this rule is attrition, which has a value of yes. This rule suggests that the employee is disengaged

or committed to their work or the company. The input variables may indicate that the employee is new, inexperienced, and isolated and does not feel valued or challenged by their work. This rule can help us identify employees at risk of leaving and take actions to improve their environmental satisfaction, provide them with more training and support, and encourage them to travel more or work overtime if possible.

5.3.7 Rule on yearsatcompany , department, worklifebalance, environmentsatisfaction, avg_monthly_hrs, businesstravel, totalworkingyears, over time

RULE: \$YearsAtCompany\$ <= 0.5 AND \$Department\$ = "Research & Development" AND \$WorkLifeBalance\$ > 2.5 AND \$EnvironmentSatisfaction\$ > 1.5 AND \$avg_monthly_hrs\$ <= 274.0 AND \$BusinessTravel\$ = "Travel_Rarely" AND \$TotalWorkingYears\$ <= 1.5 AND \$OverTime\$ = "No"

This rule means that if an employee has worked at the company for less than or equal to 0.5 years, belongs to the research and development department, and has a high work-life balance level, which means they are satisfied with their time allocation between work and personal activities, has a high environment satisfaction level, which means they are happy with their work surroundings, has average monthly working hours of less than or equal to 274.0 hours, rarely travels for business purposes, has less than or equal to 1.5 years of total working experience, and does not work overtime, then the employee will leave the organization. The output variable for this rule is attrition, which has a value of

yes. This rule suggests that the employee is not loyal or attached to their work or the company. The input variables may indicate that the employee is new, inexperienced, and comfortable but does not feel motivated or challenged by their work. This rule can help us identify employees who are at risk of leaving and take actions to increase their commitment, provide them with more feedback and recognition, and encourage them to travel more or work overtime if possible.

5.3.7 Rule on years at company, department, work-life balance, environment satisfaction, avg_monthly_hrs, business travel, total working year, overtime

RULE: \$YearsAtCompany\$ <= 0.5 AND \$Department\$ = "Research & Development" AND \$WorkLifeBalance\$ > 2.5 AND \$EnvironmentSatisfaction\$ > 1.5 AND \$avg_monthly_hrs\$ <= 274.0 AND \$BusinessTravel\$ = "Travel_Rarely" AND \$TotalWorkingYears\$ <= 1.5 AND \$OverTime\$ = "No"

This rule means that if an employee has an age of less than or equal to 32.5 years, has a percent salary hike of less than or equal to 12.5%, has a job level of 3 or higher, has an age of less than or equal to 45.5 years, has worked at the company for one year, has a high work-life balance level, which means they are satisfied with their time allocation between work and personal activities, has a stock options level of 0, has more than 1.5 years of total working experience, and does not work overtime, then the employee will leave the organization. The output variable for this rule is attrition, which has a value of

yes. This rule suggests that the employee is unhappy or dissatisfied with their salary or career progression. The input variables may indicate that the employee is young, experienced, and skilled but feels underpaid or underpromoted by the company. This rule can help us identify employees who are at risk of leaving and take action to increase their salary, offer them more stock options, or provide them with more opportunities for advancement.

5.3.8 Rule on avg_monthly_hrs, job satisfaction, age, department, years at the company, stcoplvl, total working years, over time

RULE: \$avg_monthly_hrs\$ <= 176.5 AND \$JobSatisfaction\$ <= 1.5 AND \$Age\$ <= 30.5 AND \$Department\$ = "Sales" AND \$YearsAtCompany\$ <= 29.0 AND \$StcOpLvl\$ = "1" AND \$TotalWorkingYears\$ > 1.5 AND \$OverTime\$ = "No"

This rule means that if an employee has average monthly working hours of less than or equal to 176.5 hours, has a low job satisfaction level, which means they are unhappy with their work content or conditions, has an age of less than or equal to 30.5 years, belongs to the sales department, has worked at the company for less than or equal to 29 years, has a stock options level of 1, has more than 1.5 years of total working experience, and does not work overtime; then the employee will leave the organization. The output variable for this rule is attrition, which has a value of yes. This rule suggests that the employee is bored or frustrated with their work or the company culture. The input variables may indicate that the employee is young, experienced, and rewarded but feels

uninterested or unchallenged by their work. This rule can help us identify employees at risk of leaving and take action to improve their job satisfaction, provide them with more feedback and recognition, and encourage them to work more hours or overtime if possible.

5.3.9 Rule on percent salary hike, gender, education, stcoplvl, worked at comp, job level, and overtime

RULE: \$PercentSalaryHike\$ <= 12.5 AND \$Gender\$ = "Female" AND \$Education\$ <= 3.5 AND \$StcOpLvl\$ = "1" AND \$WorkedAtComp\$ = "1" AND \$JobLevel\$ <= 1.5 AND \$OverTime\$ = "Yes"

This rule means that if an employee has a percent salary hike of less than or equal to 12.5%, is female, has an education level of less than or equal to 3.5, which means they have a bachelor's degree or lower, has a stock options level of 1, has worked at the company for one year, has a job level of 1 or 2, and works overtime, then the employee will leave the organization. The output variable for this rule is attrition, which has a value of yes. This rule suggests that the employee is unhappy or dissatisfied with their salary or career progression. The input variables may indicate that the employee is underpaid, undereducated, or underpromoted by the company. This rule can help us identify employees who are at risk of leaving and take action to increase their salary, offer them more stock options, or provide them with more opportunities for advancement.

5.3.10 Rule on YearsWithCurrManager, YearsSinceLastPromotion, WorkedAtComp, DistanceFromHome, StcOpLvl, JobLevel, Overtime

RULE: \$YearsWithCurrManager\$ <= 6.5 AND \$YearsSinceLastPromotion\$ <= 0.5 AND \$WorkedAtComp\$ = "1" AND \$DistanceFromHome\$ <= 23.5 AND \$StcOpLvl\$ = "0" AND \$JobLevel\$ > 1.5 AND \$OverTime\$ = "Yes"

This rule means that if an employee has worked with their current manager for less than or equal to 6.5 years, has not been promoted in the last 0.5 years, has worked at the company for one year, lives within 23.5 units of distance from home, has a stock options level of 0, has a job level of 2 or higher, and works overtime; then the employee will leave the organization. The output variable for this rule is attrition, which has a value of yes. This rule suggests that the employee is unhappy or dissatisfied with their manager or career progression. The input variables may indicate that the employee is experienced, skilled, and loyal but feels underappreciated or undervalued by their manager or the company. This rule can help us identify employees at risk of leaving and take action to improve their relationship with their manager, offer them more stock options, or provide them with more opportunities for advancement.

5.3.11 Rule on monthly income, worked at the company, job level, over time

RULE: \$Monthly income\$ <= 8392.0 AND \$WorkedAtComp\$ = "2" AND \$JobLevel\$ <= 1.5 AND \$OverTime\$ = "Yes"

This rule means that if an employee has a monthly income of less than or equal to 8392.0 units, has worked at the company for two years, has a job level of 1 or 2, and works overtime; the employee will stay at the organization. The output variable for this rule is attrition, which has a value of no. This rule suggests that the employee is satisfied or content with their job or the company benefits. The input variables may indicate that the employee is paid fairly, loyal, hardworking, and feels rewarded or motivated by their work. This rule can help us identify employees who are not at risk of leaving and take action to maintain their satisfaction, provide them with more feedback and recognition, and encourage them to continue working overtime if possible.

5.3.12 Rule on Decision_skill_possess, WorkedAtComp, DistanceFromHome, StcOpLvl, JobLevel, and OverTime

RULE: \$Decision_skill_possess\$ = "Analytical" AND \$WorkedAtComp\$ = "4" AND \$DistanceFromHome\$ <= 23.5 AND \$StcOpLvl\$ = "0" AND \$JobLevel\$ > 1.5 AND \$OverTime\$ = "Yes"

This rule means that if an employee has analytical decision skills, which means they can think logically and rationally, has worked at the company for four years, lives

within 23.5 units of distance from home, has a stock options level of 0, has a job level of 2 or higher, and works overtime, then the employee will stay at the organization. The output variable for this rule is attrition, which has a value of no. This rule suggests that the employee is engaged or committed to their work or the company. The input variables may indicate that the employee is intelligent, ambitious, talented, and feels challenged or fulfilled by their work. This rule can help us identify employees who are not at risk of leaving and take actions to maintain their engagement, provide them with more feedback and recognition, and encourage them to continue working overtime if possible.

5.3.13 Rule On Worked At Company, Distance From Home, Stock Options Level, Job Level, And Overtime

RULE: \$WorkedAtComp\$ = "6" AND \$DistanceFromHome\$ <= 23.5 AND \$StcOpLvl\$ = "0" AND \$JobLevel\$ > 1.5 AND \$OverTime\$ = "Yes"

This rule means that if an employee has worked at the company for six years, lives within 23.5 units of distance from home, has a stock options level of 0, has a job level of 2 or higher, and works overtime, then the employee will stay at the organization. The output variable for this rule is attrition, which has a value of no. This rule suggests that the employee is loyal or attached to their work or the company. The input variables may indicate that the employee is experienced, skilled, hardworking, and feels valued or rewarded. This rule can help us identify employees who are not at risk of leaving and take

action to maintain their loyalty, provide them with more feedback and recognition, and encourage them to continue working overtime if possible.

5.3.14 Rule on average monthly hours, total working years, worked at company, distance from home, stock options level, job level, and over time

RULE: \$avg_monthly_hrs\$ > 251.5 AND \$TotalWorkingYears\$ <= 14.0 AND \$WorkedAtComp\$ = "3" AND \$DistanceFromHome\$ <= 23.5 AND \$StcOpLvl\$ = "0" AND \$JobLevel\$ > 1.5 AND \$OverTime\$ = "Yes"

This rule means that if an employee has an average monthly working hours of more than 251.5 hours, has less than or equal to 14.0 years of total working experience, has worked at the company for three years, lives within 23.5 units of distance from home, has a stock options level of 0, has a job level of 2 or higher, and works overtime; then the employee will stay at the organization. The output variable for this rule is attrition, which has a value of no. This rule suggests that the employee is motivated or passionate about their work or the company. The input variables may indicate that the employee is productive, capable, ambitious, and feels challenged or fulfilled by their work. This rule can help us identify employees who are not at risk of leaving and take action to maintain their motivation, provide them with more feedback and recognition, and encourage them to continue working overtime if possible.

5.3.15 Rule On N_Projects, Monthly Income, Distancefromhome, Totalworkingyears, Stcoplvl, Joblevel, And Overtime

RULE: \$n_projects\$ > 2.5 AND \$Monthly income\$ > 23427.0 AND \$DistanceFromHome\$ <= 27.0 AND \$TotalWorkingYears\$ > 5.5 AND \$StcOpLvl\$ = "1" AND \$JobLevel\$ > 1.5 AND \$OverTime\$ = "Yes"

This rule means that if an employee has more than 2.5 projects, has a monthly income greater than 23427.0 units, lives within 27.0 units of distance from home, has more than 5.5 years of total working experience, has a stock options level of 1, has a job level of 2 or higher, and works overtime, then the employee will stay at the organization. The output variable for this rule is attrition, which has a value of no. This rule suggests that employees are satisfied or content with their work or the company benefits. The input variables may indicate that the employee is well-paid, experienced, and skilled and feels rewarded or motivated by their work. This rule can help us identify employees who are not at risk of leaving and take action to maintain their satisfaction, provide them with more feedback and recognition, and encourage them to continue working overtime if possible.

5.3.16 Rule on the department, work-life balance, environment satisfaction, avg monthly hours, business travel, total working years, and overtime

RULE: \$Department\$ = "Sales" AND \$WorkLifeBalance\$ > 2.5 AND \$EnvironmentSatisfaction\$ > 1.5 AND \$avg_monthly_hrs\$ <= 274.0 AND \$BusinessTravel\$ = "Travel_Rarely" AND \$TotalWorkingYears\$ <= 1.5 AND \$OverTime\$ = "No"

This rule means that if an employee belongs to the sales department, has a high work-life balance level, which means they are satisfied with their time allocation between work and personal activities, has a high environment satisfaction level, which means they are happy with their work surroundings, has average monthly working hours of less than or equal to 274.0 hours, rarely travels for business purposes, and has less than or equal to 1.5 years of total working experience, then the employee will stay at the organization. The output variable for this rule is attrition, which has a value of no. This rule suggests that employees are comfortable or happy with their work or the company culture. The input variables may indicate that the employee is new, inexperienced, and relaxed and feels interested or fulfilled by their work. This rule can help us identify employees who are not at risk of leaving and take actions to maintain their comfort, provide them with more feedback and recognition, and encourage them to travel more or work more hours if possible.

5.3.17 Rule On Percentsalaryhike, Joblevel, Age, Workedatcomp, Work life balance, Stcoplvl, Totalworkingyears, And Overtime

RULE: \$PercentSalaryHike\$ > 12.5 AND \$JobLevel\$ > 2.5 AND \$Age\$ <= 45.5 AND \$WorkedAtComp\$ = "1" AND \$WorkLifeBalance\$ > 1.5 AND \$StcOpLvl\$ = "0" AND \$TotalWorkingYears\$ > 1.5 AND \$OverTime\$ = "No"

This rule means that if an employee has a percent salary hike of more than 12.5%, has a job level of 3 or higher, has an age of less than or equal to 45.5 years, has worked at the company for one year, has a high work-life balance level, which means they are satisfied with their time allocation between work and personal activities, has a stock options level of 0, and has more than 1.5 years of total working experience. The employee will stay at the organization. The output variable for this rule is attrition, which has a value of no. This rule suggests the employee is happy or satisfied with their salary or career progression. The input variables may indicate that the employee is well-paid, experienced, and skilled and feels rewarded or motivated by their work. This rule can help us identify employees who are not at risk of leaving and take actions to maintain their happiness, provide them with more feedback and recognition, and offer them more stock options if possible.

5.3.18 Rule on work-life balance, worked at company, age, department, years at the company, StcOpLvl, TotalWorkingYears, and OverTime

RULE: \$WorkLifeBalance\$ > 2.5 AND \$WorkedAtComp\$ = "0" AND \$Age\$ > 30.5 AND \$Department\$ = "Sales" AND \$YearsAtCompany\$ <= 29.0 AND \$StcOpLvl\$ = "1" AND \$TotalWorkingYears\$ > 1.5 AND \$OverTime\$ = "No"

This rule means that if an employee has a high work-life balance level, which means they are satisfied with their time allocation between work and personal activities, has not worked at the company yet, has an age of more than 30.5 years, belongs to the sales department, has worked at the company for less than or equal to 29 years, has a stock options level of 1, and has more than 1.5 years of total working experience. The employee will stay at the organization. The output variable for this rule is attrition, which has a value of no. This rule suggests that employees are comfortable or happy with their work or the company culture. The input variables may indicate that the employee is new, experienced, rewarded, and feels interested or fulfilled by their work. This rule can help us identify employees who are not at risk of leaving and take actions to maintain their comfort, provide them with more feedback and recognition, and encourage them to work more hours or overtime if possible.

5.3.19 Rule on gender, years at company, stcoplvl, total working years, and over time

RULE: \$Gender\$ = "Male" AND \$YearsAtCompany\$ > 29.0 AND \$StcOpLvl\$ = "1" AND \$TotalWorkingYears\$ > 1.5 AND \$OverTime\$ = "No"

This rule means that if an employee is male, has worked at the company for more than 29 years, has a stock options level of 1, and has more than 1.5 years of total working experience; then the employee will stay at the organization. The output variable for this rule is attrition, which has a value of no. This rule suggests that the employee is loyal or

attached to their work or the company. The input variables may indicate that the employee is experienced, skilled, and rewarded and feels valued or respected by their work. This rule can help us identify employees who are not at risk of leaving and take action to maintain their loyalty, provide them with more feedback and recognition, and offer them more stock options if possible.

5.3.20 Rule on years with current manager, worked at the company, stcoplvl, total working years, and over time

RULE: \$YearsWithCurrManager\$ <= 2.5 AND \$WorkedAtComp\$ = "7" AND \$StcOpLvl\$ = "3" AND \$TotalWorkingYears\$ > 1.5 AND \$OverTime\$ = "No"

This rule means that if an employee has worked with their current manager for less than or equal to 2.5 years, has worked at the company for seven years, has a stock options level of 3, and has more than 1.5 years of total working experience; then the employee will stay at the organization. The output variable for this rule is attrition, which has a value of no. This rule suggests that employees are satisfied with their manager's or company's benefits. The input variables may indicate that the employee is experienced, skilled, and rewarded and feels appreciated or supported by their manager or the company. This rule can help us identify employees who are not at risk of leaving and take actions to maintain their satisfaction, provide them with more feedback and recognition, and offer them more stock options if possible.

5.3 RETENTION STRATEGIES

The report compares different prediction models for employee attrition based on various attributes. The models used are random forest classifier and decision tree analysis. The results show that employee salary-related attributes are the most critical factors influencing employee attrition, followed by employee work and organizational attributes, and lastly, employee personal attributes. Employees are likelier to leave the organization if they are unhappy with their pay, work environment, or career opportunities. The report suggests that the organization should improve employee satisfaction and retention by addressing these issues. Retention strategies are the methods and practices that aim to keep employees satisfied and loyal to the organization by addressing their needs and expectations.

5.3.1 Employee Salary-Related Retention Strategies:

Employee salary-related retention strategies are methods that organizations use to keep employees for as long as possible by offering competitive and fair compensation. These strategies can help reduce employee turnover, increase employee satisfaction, and improve organizational performance.

Some of the employee salary-related retention strategies are:

- **Offering competitive base salaries or hourly wages** that match or exceed the market rate and the cost of living in the area. It can help employees feel valued and motivated to work hard¹
- **Provide regular raises and bonuses** based on performance, experience, and inflation. It can help employees feel rewarded and recognized for their contributions and achievements.
- **It offers employee stock options (ESOPs)** or other forms of equity compensation that give employees a stake in the company's success and future growth. It can help employees feel invested and loyal to the company.
- **Providing other perks** such as health insurance, retirement plans, education assistance, childcare support, or travel allowances can enhance employees' quality of life and well-being. These perks can also help employees save money and reduce stress²
- **Conducting frequent salary reviews** and market research ensures that employees are paid fairly and competitively according to their skills, roles, and responsibilities. It can help employees feel respected and appreciated and prevent them from seeking better opportunities elsewhere.

These employees' salary-related retention strategies are applied to make data-driven decisions for employee attrition and retention strategies.

5.3.2 Employee Non-Monetary Retention Strategies:

Employee non-monetary retention strategies are methods that organizations use to keep employees for as long as possible by offering them rewards and incentives that are not related to money. These strategies can help increase employee motivation, recognition, and loyalty.

Some of the employee non-monetary retention strategies are:

- **Flexibility at work** allows employees to decide when and where they work. It can help employees balance their personal and professional lives, reduce stress, and improve productivity.
 - **Rewards and recognition** acknowledge and appreciate employees' achievements, efforts, and contributions. It can help employees feel valued and respected and boost their self-esteem and morale. Rewards and recognition can be tangible (such as gift cards, trophies, or certificates) or intangible (such as praise, feedback, or thank-you notes)
 - **Provide an extra day off** or a paid leave for employees who perform exceptionally well, complete a project on time, or reach a milestone. It can help employees relax, recharge, and enjoy their time.
 - **Provide time for volunteer work** or social responsibility initiatives that align with the organization's values and mission. It can help employees feel connected to a greater purpose, develop new skills, and positively impact the community.
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- **Provide extensive training plans** or learning opportunities that help employees develop their skills, knowledge, and competencies. It can help employees grow their potential, achieve their career goals, and stay updated on the latest trends and best practices.
- **One-on-one lunch** or coffee with a manager, leader, or mentor allows employees to share their ideas, opinions, feedback, or concerns. It can help employees build rapport, trust, and communication with their superiors and receive guidance and support.
- **Experiential rewards:** Experiential rewards such as trips, events, activities, or experiences that create memorable moments for employees. It can help employees have fun, bond with their colleagues, and enrich their lives.
- **Offer to mentor an employee** or assign a mentor who can coach, advise, and inspire them. It can help employees learn from the experts, overcome challenges, and advance their careers.

These are some of the employee non-monetary retention strategies that Organizations can use to make data-driven decisions for employee attrition and retention strategies.

5.3.3 Employee Work-Related Retention Strategies:

Organizations use methods to keep employees for as long as possible by offering them meaningful and satisfying work experiences. These strategies can help reduce

employee turnover, increase employee engagement, and improve organizational performance.

Some of the employee work-related retention strategies are:

- **Providing effective leadership** that inspires, supports, and empowers employees. Leaders should communicate the vision and goals of the organization, provide regular feedback and recognition, and foster a culture of trust and collaboration.
- **Increase employee engagement** by involving employees in decision-making, soliciting their ideas and opinions, and giving them autonomy and ownership over their work. Engaged employees are more committed, productive, and loyal to the organization.
- **Offer professional development opportunities** such as training, coaching, mentoring, or career advancement. It can help employees learn new skills, grow their potential, and achieve their career goals.
- **Designing products people love** by conducting market research, user experience testing, concept testing, and brand analysis. It can help employees create products that meet customer needs, solve problems, and generate value.
- **A positive work environment** promotes well-being, diversity, inclusion, and social responsibility. It can help employees feel happy, healthy, safe, and respected.

These are some of the employee work-related retention strategies that we can use to make data-driven decisions for employee attrition and retention strategies.

5.3.4 Employee Personal-Related Retention Strategies

Organizations use methods to keep employees for as long as possible by offering them support and care for their personal needs and goals. These strategies can help increase employee well-being, loyalty, and satisfaction.

Some of the employee personal-related retention strategies are:

- **Encourage taking time off** or vacations that allow employees to relax, recharge, and enjoy their time. It can help employees reduce stress, prevent burnout, and improve their health and happiness.
 - **Focus on value rather than time spent** on work, and be flexible in the hours we require employees to work. It can help employees balance their personal and professional lives, manage their priorities, and work more efficiently and effectively.
 - **Provide personalized employee support** such as counseling, coaching, mentoring, or wellness programs that help employees cope with their personal or professional challenges, improve their mental and emotional health, and achieve their potential.
 - **Create a people-first workplace** that values, respects, and empowers employees as individuals. It can help employees feel connected, engaged, and appreciated by the organization and their colleagues.
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- **Make meaningful connections at work** by fostering a culture of trust, collaboration, and communication. It can help employees build rapport, friendship, and teamwork with their superiors and peers.
- **Recognize and appreciate their hard work** by providing regular feedback, praise, or rewards for their achievements, efforts, and contributions. It can help employees feel valued, respected, and motivated to work hard.
- **Create career advancement opportunities** such as training, development, or promotion that help employees learn new skills, grow their potential, and achieve their career goals. It can help employees feel challenged, inspired, and loyal to the organization.
- **Provide competitive compensation** such as salaries, bonuses, or benefits that match or exceed the market rate and the cost of living in the area. It can help employees feel rewarded and secure in their financial situation.

Organizations can use These employees' personal-related retention strategies to make data-driven decisions for employee attrition and retention strategies.

5.3.5 Few Other Retention Strategies

Some of the other employee retention strategies that we can use to make data-driven decisions for employee attrition and retention strategies are:

- **Let employees work from home** or offer remote or hybrid work options that suit their preferences and needs. It can help employees save time and money on commuting, reduce stress, and improve their work-life balance.
 - **Provide flexible scheduling and reduced workdays** that allow employees to adjust their working hours or days according to their personal or professional obligations. It can help employees manage their priorities, avoid burnout, and increase their productivity and happiness.
 - **Set up mentorship and training programs** that help employees develop their skills, knowledge, and competencies. It can help employees learn from the experts, overcome challenges, and advance their careers.
 - **Encourage a healthy work-life balance** by promoting wellness initiatives, providing health benefits, or offering fitness incentives. It can help employees improve their physical and mental health, prevent illness, and boost their energy and mood.
 - **Design products people love** by conducting market research, user experience testing, concept testing, and brand analysis. It can help employees create products that meet customer needs, solve problems, and generate value.
 - **Provide additional benefits** such as vacation/holiday benefits, paid personal time off, education assistance, childcare support, or travel allowances that can enhance employees' quality of life and well-being. These benefits can also help employees save money and reduce stress.
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CHAPTER VI

SUMMARY, IMPLICATIONS, AND RECOMMENDATIONS

6.1 SUMMARY

- Employee attrition is the voluntary or involuntary loss of employees from an organization without being immediately replaced. Employee attrition can have various causes and consequences for the organization and the employees. Employee attrition can also measure by the attrition rate, which is the percentage of employees who leave the organization over time.
 - Employee attrition is a common and challenging problem in the IT sector, which employs more than three million people in India. The IT sector faces high employee attrition rates ranging from 15-18 percent. Various factors can influence employee attrition in the IT sector.
 - **Dissatisfaction with pay:** Employees who feel underpaid or unfairly compensated may leave the organization for better opportunities.
 - **Lack of career advancement:** Employees who feel stuck or stagnant may leave the organization for more growth and development opportunities.
 - **Poor employee relations:** Employees who feel isolated, ignored, or mistreated by their colleagues or managers may leave the organization for more supportive and positive work environments.
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- **Improper schedule:** Employees who face long working hours, irregular shifts, or frequent travel may leave the organization for more flexible and balanced work arrangements.
 - **Poor working conditions:** Employees who face stressful, unsafe, or unhealthy work conditions may leave the organization for more comfortable and conducive work environments.
 - **Job-related stress:** Employees who face high work pressure, unrealistic expectations, or complex tasks may leave the organization for more manageable and enjoyable work roles.
 - **Higher education:** Employees who pursue higher education or professional certifications may leave the organization for more academic or career opportunities.
 - **Problems with management:** Employees who face poor leadership, communication, or feedback from their managers may leave the organization for more effective and responsive management⁴.
 - **Location of the organization:** Employees who face long commutes, relocation issues, or personal preferences may leave the organization for more convenient and suitable locations.
 - **Maternity:** Employees who face pregnancy, childbirth, or childcare issues may leave the organization for more family-friendly policies and practices.
 - **Best offer next door:** Employees who receive attractive offers from competitors or other industries may leave the organization for more lucrative and appealing prospects.
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- **Overseas opportunities:** Employees who receive global offers or aspire to work abroad may leave the organization for more international and diverse experiences.
- **Shifting of cities due to marriage, family, and personal problems:** Employees facing marital, familial, or personal issues that require moving to another city may leave the organization for personal and emotional reasons.
- Employee attrition can have various effects on the organization and the employees. Some of the effects are:

For the organization:

- **Loss of productivity and quality:** Employee attrition can result in reduced output and performance due to the loss of skilled and experienced employees.
 - **Loss of customer satisfaction and loyalty:** Employee attrition can result in poor service and delivery due to the loss of knowledgeable and familiar employees
 - **Loss of competitive advantage and innovation:** Employee attrition can result in loss of talent and creativity due to the loss of valuable and unique employees.
 - **Increased recruitment and training costs:** Employee attrition can increase expenses for hiring and developing new employees.
 - **Increase in employee turnover:** Employee attrition can result in increased employee turnover due to low morale, engagement, and retention among existing employees.
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For the employees:

- **Loss of income and benefits:** Employee attrition can result in loss of salary, incentives, and perks due to leaving the organization.
- **Loss of career opportunities and growth:** Employee attrition can result in loss of learning, development, and promotion due to leaving the organization.
- **Loss of social support and network:** Employee attrition can result in losing friends, mentors, and contacts due to leaving the organization.
- **Increased stress and uncertainty:** Employee attrition can increase anxiety, insecurity, and confusion due to leaving the organization.
- **Increase in job dissatisfaction and regret:** Employee attrition can result in increased unhappiness, frustration, and remorse due to leaving the organization.
- Various solutions based on data-driven decision-making and people analytics can prevent or reduce employee attrition. Data-driven decision-making and people analytics can help employers design and implement retention strategies based on data and evidence. Data-driven decision-making and people analytics can also help employers monitor and evaluate the impact of retention strategies on employee outcomes.

Some of the solutions are:

- **Offering competitive and fair compensation and benefits:** Employers can use data and analytics to benchmark their pay and benefits with the market and industry
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standards. Employers can also use data and analytics to customize and personalize their pay and benefits according to employee preferences and needs.

- **Providing growth and development opportunities:** Employers can use data and analytics to identify and address their employees' skill gaps and career aspirations. Employers can also use data and analytics to provide employees with training, coaching, mentoring, feedback, and recognition.
 - **Enhancing employee engagement and satisfaction:** Employers can use data and analytics to measure and improve their employees' engagement and satisfaction levels. Employers can also use data and analytics to create a positive, supportive, and inclusive work culture for their employees.
 - **Providing flexible work arrangements:** Employers can use data and analytics to assess and accommodate the work-life balance needs of their employees. Employers can also use data and analytics to offer employees remote, flexible, part-time, or hybrid work options.
 - **Enhancing employee empowerment and autonomy:** Employers can use data and analytics to empower and involve their employees in decision-making, problem-solving,
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and innovation. Employers can also use data and analytics to give their employees more freedom, responsibility, and ownership of their work.

- **Employee attrition is a complex and multifaceted problem that requires a holistic and strategic approach.** By using data-driven decision-making and people analytics, employers can better understand, predict, prevent, and reduce employee attrition in the IT sector. By doing so, employers can save costs, time, and resources and improve productivity, quality, customer satisfaction, competitive advantage, innovation, employee morale, engagement, retention, loyalty, happiness, well-being, performance, and career growth. By using data-driven decision-making and people analytics, employers can create a win-win situation for the organization and the employees.
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6.2 IMPLICATIONS

Employee attrition is a critical problem and a considerable risk for organizations, affecting their productivity, continuity, and competitiveness. Organizations must use data-driven decision-making and people analytics to reduce attrition and retain talent. People analytics systematically uses data and analytics to inform and improve HR and talent management decisions. It involves collecting, analyzing, and interpreting data on employee behavior, attitudes, and performance to drive business results and improve the employee experience.

Some of the implications of employee attrition for data-driven decision-making and people analytics are:

- Organizations need to use big data and deep data to support people analytics for employee attrition prediction. Big data refers to the large volume and variety of data generated by employees, while deep data refers to the quality and relevance of data for answering specific questions. By using big and deep data, organizations can identify the most critical factors influencing employee attrition, compare different models for predicting employee attrition, generate decision rules for identifying employees who are likely to leave and provide recommendations for retention strategies based on the findings.
 - Organizations need to use data visualization and storytelling to communicate the results of people analytics for employee attrition to different stakeholders. Data visualization refers to using charts, graphs, maps, and other visual elements to present data appealingly and understandably. Storytelling refers to using narrative techniques to convey the
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meaning and implications of data compellingly and engagingly. Using data visualization and storytelling, organizations can highlight the main findings and insights from people analytics, explain the causes and consequences of employee attrition, and persuade stakeholders to take action based on the evidence.

- Organizations must use ethical and legal principles to guide their use of data and analytics for employee attrition. Ethical principles refer to the values and norms that govern the conduct of people analytics, such as respect, fairness, transparency, accountability, and privacy. Legal principles refer to the laws and regulations that apply to collecting, processing, storing, and sharing employee data, such as GDPR, HIPAA, and CCPA. By using ethical and legal principles, organizations can ensure that their data and analytics for employee attrition are responsible, trustworthy, and compliant.

Conclusion

Employee attrition is a significant challenge for organizations in the era of data science and big data analytics. To address this challenge, organizations must use data-driven decision-making and people analytics to understand and improve their talent management practices. However, using data and analytics for employee attrition also affects how organizations collect, analyze, interpret, communicate, and use employee data. Therefore, organizations need to use big data and deep data to support people analytics for employee attrition prediction, data visualization and storytelling to communicate the results of people analytics for employee attrition; and ethical and legal principles to guide their use of data and analytics for employee attrition.

6.3 RECOMMENDATIONS FOR FUTURE RESEARCH

Data-driven decision-making and people analytics are essential tools for understanding and improving employee attrition, a critical problem and considerable risk for organizations. However, there are still many gaps and challenges in the current research and practice of using data and analytics for employee attrition.

Therefore, some possible recommendations for future research are:

- Expand the scope and quality of data and analytics for employee attrition prediction. Current research mainly uses big and deep data to identify the most critical factors influencing employee attrition, such as monthly income, overtime, and age. However, other factors may also affect employee attrition, such as leadership, occupational health, safety, security, hazardous working environment, and non-monetary benefits allocation. Future research should collect and analyze more diverse and relevant data sources to capture these factors and their interactions. Future research should also use more advanced and robust methods and techniques to ensure the validity and reliability of the data and analytics.
 - Improve the communication and interpretation of data and analytics for employee attrition to different stakeholders. Current research mainly focuses on data visualization and storytelling to present data and analytics results for employee attrition, such as the importance of factors, the accuracy of models, the decision rules, and the insights from exploratory data analysis. However, other aspects may also need to be communicated and
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interpreted, such as the data and analytics limitations, assumptions, uncertainties, trade-offs, and implications. Future research should use more effective and engaging ways to convey these aspects and help stakeholders understand and use the data and analytics for employee attrition.

- Apply ethical and legal principles to guide the use of data and analytics for employee attrition. Current research mainly focuses on using ethical and legal principles to ensure that the use of data and analytics for employee attrition is responsible, trustworthy, and compliant. However, other issues may also arise from using data and analytics for employee attrition, such as privacy, consent, fairness, transparency, accountability, bias, and discrimination. Future research should address these issues and develop frameworks and guidelines to help organizations use data and analytics for employee attrition ethically and legally.

Data-driven decision-making and people analytics are powerful tools for addressing the challenge of employee attrition. However, they also affect how organizations collect, analyze, interpret, communicate, and use employee data. Therefore, future research should expand the scope and quality of data and analytics for employee attrition prediction, improve the communication and interpretation of data and analytics for employee attrition, and apply ethical and legal principles to guide data and analytics for employee attrition.

6.4 CONCLUSION

This thesis has demonstrated how machine learning models can support data-driven decision-making and people analytics in organizations, especially in the context of employee churn. The thesis identified the most critical factors affecting employee attrition, such as job satisfaction, work-life balance, salary, and bonus, by applying machine learning techniques such as logistic regression, decision tree, random forest, and support vector machine. The thesis also proposed a rule-based decision framework that can help managers and HR professionals to predict and prevent employee turnover by providing personalized recommendations and interventions based on the employee's profile and risk level. The thesis has shown that machine learning models can provide valuable insights and solutions for organizations that want to retain their talent and improve their performance. However, the thesis also acknowledged the limitations and challenges of using machine learning models for people analytics, such as data quality, ethical issues, and human factors. Therefore, the thesis suggested some directions for future research and improvement, such as incorporating more variables and data sources, exploring other machine learning methods and evaluation metrics, and enhancing the interpretability and explainability of the models.

Machine learning is a branch of artificial intelligence that enables systems to learn from data and improve performance without explicit programming. Organizations

can use machine learning to improve employee engagement, which is employees' commitment, involvement, and satisfaction towards their work and organization.

Some of the ways that machine learning can improve employee engagement are:

- **Personalizing customer service:** Machine learning can help organizations provide personalized and responsive customer service using natural language processing, chatbots, sentiment analysis, and recommendation systems. It can improve customer satisfaction, loyalty, employee motivation, and productivity.
 - **Improving customer retention:** Machine learning can help organizations predict and prevent customer churn by analyzing customer behavior, preferences, feedback, and transactions. It can help organizations tailor their offers, services, and interactions to retain customers and increase. It can also boost employee morale and performance by reducing attrition and increasing revenue.
 - **Hiring the right people:** Machine learning can help organizations streamline and optimize their hiring process by using resume screening, talent sourcing, skill assessment, and interview scheduling tools. It can help organizations find the best candidates for their roles, reduce hiring costs and time, and improve hiring quality and diversity. It can also enhance employee engagement by matching employees with the right jobs, teams, and cultures.
 - **Creating personalized learning and development experiences:** Machine learning can help organizations design and deliver personalized learning and development programs
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for employees using adaptive learning, gamification, microlearning, and feedback mechanisms. It can help organizations improve employee skills, knowledge, and performance, as well as employee retention, satisfaction, and growth.

- **Automating mundane tasks:** Machine learning can help organizations automate and streamline various mundane and repetitive tasks such as data entry, report generation, and invoice processing. It can help organizations save time, money, and resources and reduce errors and risks. It can also improve employee engagement by freeing employees to focus on more creative, challenging, and meaningful work.
- **Removing bias by increasing diversity:** Machine learning can help organizations remove bias and increase diversity in their workforce by using fair and transparent hiring, promotion, and compensation algorithms. It can help organizations create a more inclusive and equitable work environment that respects and values different perspectives, backgrounds, and identities. It can also improve employee engagement by fostering a sense of belonging, trust, and respect.

The main findings of the thesis were:

- Data-driven decision-making and decision-rule-based people analytics are practical tools for predicting and preventing employee churn. They can help organizations identify the most critical factors influencing employee attrition, compare different models for predicting employee attrition, generate decision rules for identifying employees likely to leave, and provide recommendations for retention strategies based on the findings.
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- Work-related, salary-related, and monetary-related problems are the most impulsive factors for employee attrition. Employees who are overworked, micro-managed, improperly compensated, and lack career growth opportunities are more likely to leave the organization. Employees with low income, low job satisfaction, low-performance rating, low percent salary hike, and few working years in the company are also more likely to leave the organization.
- Organizations can use data-driven decision-making and decision-rule-based people analytics to improve talent management practices and reduce employee churn. They can use big data and deep data to support people analytics for employee attrition prediction, data visualization, and storytelling to communicate the results of people analytics for employee attrition, and ethical and legal principles to guide data and analytics for employee attrition.

The main contributions of the thesis were:

- The thesis proposed a novel approach using data-driven decision-making and decision-rule-based people analytics to identify employee churn. The approach combined mixed methods, machine learning, deep learning, ensemble learning, and decision tree analysis to construct a relevant employee attrition model and generate decision rules based on various conditions and attributes of the employees.
 - The thesis applied the proposed approach to large-sized and medium-sized simulated human resources datasets and then a real small-sized dataset from a total of 450 responses.
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Compared to previous solutions, the approach achieved higher accuracy (0.96, 0.98, and 0.99, respectively) for the three datasets.

- The thesis revealed several insights about the characteristics and preferences of the employees who left or stayed in the company. The thesis also provided recommendations for retention strategies based on the findings.

The main limitations of the thesis were:

- The thesis used a small sample size and did not consider external factors such as market conditions or competitor actions. It may limit the generalizability and validity of the findings.
- The thesis did not validate or test the models or rules on new data. It may affect the reliability and robustness of the findings.
- The thesis did not consider other factors affecting employee attrition, such as leadership, occupational health, safety, security, hazardous working environment, and non-monetary benefits allocation. It may omit some essential aspects of employee attrition.

The main recommendations for future research are:

- Future research should use a more significant and diverse data set to capture more factors and their interactions that influence employee attrition. Future research should also use more advanced and robust methods and techniques to ensure the validity and reliability of the data and analytics.
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- Future research should use cross-validation or hold-out methods to evaluate the models or rules on new data. Future research should also explore other methods or techniques for data analysis, such as clustering, association rule mining, or sentiment analysis.
- Future research should consider other factors affecting employee attrition, such as leadership, occupational health, safety, security, hazardous working environment, and non-monetary benefits allocation. Future research should also investigate how these factors interact with work-related, salary-related, and monetary-related problems.

In conclusion, this thesis has explored data-driven decision-making and decision-rule-based people analytics for identifying employee churn. The thesis has identified the most critical factors influencing employee attrition, compared different models for predicting employee attrition, generated decision rules for identifying employees likely to leave, and provided recommendations for retention strategies based on the findings. The thesis has also revealed several insights about the characteristics and preferences of the employees who left or stayed in the company. The thesis has contributed to the field of people analytics by proposing a novel approach for using data-driven decision-making and decision-rule-based people analytics for identifying employee churn, applying the approach to three different datasets, and providing recommendations for future research.

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