

HR ANALYTICS AND HR DECISIONS IN SELECT BANKS OF INDIA

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DECLARATION

I, hereby declared that the presented work in the thesis entitled “**HR Analytics and HR Decisions in select Banks of India**” in fulfillment of degree of **Doctor of Philosophy (Ph.D.)** is outcome of research work carried out by me under the supervision Dr. Mridula Mishra working as Professor and Head of Department in Human Resource Management-I & II, in Management, Mittal School of Business of Lovely Professional University, Punjab, India. In keeping with general practice of reporting scientific observations, due acknowledgements have been made whenever work described here has been based on findings of other investigator. This work has not been submitted in part or full to any other University or Institute for the award of any degree.

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ABSTRACT

Human resource analytics is the application of a methodology and process for improving the quality of people-related decisions to enhance individual and organizational performance (Bassi et al., 2010). The global environment demands organizations to succeed in pursuing innovation to gain a competitive advantage. Professionals in human resources play a significant role in helping their firms obtain and keep a competitive advantage. It has become imperative for organizations to enhance their efficiency and effectiveness through digitization and innovative business practice. Organizations are paying more emphasis to human resources analytics (HR), as data-driven decision-making and strategy in this function are being held to a higher standard. The data-driven methodology behind human resource analytics is aligned with strategic human resource management. Human resource analytics evaluates the effectiveness of human resource practices and interventions. The application of statistical methods and procedures aims to provide meaningful insights for human resource decisions impacting business strategies and implementation.

Human resource analytics integrates data from other functions, which are internal and external to the firm. Analytics employs information technology to collect, manipulate and report data for decision-making. Analytics plays a pivotal role in human resources management in recruitment, selection, training and development, succession planning, employee retention, engagement of human resources, and remuneration with benefits. It is a very powerful tool in the hands of human resource management for adding value to the organization. HR Analytics is an evidence-based study that assists HR professionals in making rational decisions by improving human resource strategic effect on business success.

There is a growing interest among the human resource fraternity and non-human resource professionals to analyze the role of human resource analytics in human resource decision-making. Previous researches in the field provide a thorough understanding of human resource analytics, resulting in recommendations primarily on experience and

subjectivity. With strong development and maturity of enterprise resource systems, organizations are required to do more with their data (Deloitte, 2013).

The literature review chapter consists of an extensive literature review from 2003 to 2022 to examine the role of Human Resource Analytics in Human Resource Decision Making in the Banking sector in Punjab. It had been widely identified as a gap that human resource function lacks data-based decision-making and analytic capability. Human resource decisions must be based on reporting and predictions instead of intuition and experience. There was a requirement for more scientific research. Little is known about the factors influencing the need for HR Analytics in the banking sector. There was a lack of sufficient empirical evidence to support adoption of human resources analytics. Studies on the relationship between human resource analytics and successful organizational outcomes are few. Theory-based predictions of relationships are lacking. Predictive modeling-based studies and organizational studies must be available.

The studies were related to Human Resource Analytics and Human Resource Decisions. The review revealed that human resource practices were considered one of the influential factors for profitable and proficient banking operations, the creation of new banking products, and provision of better services to customers. Researchers had identified numerous HR organizational practices as significant factors in influencing performance. The findings stated that innovative HR practices would benefit the banks to gain competitive edge in the global market. The innovative practices such as availability of bank communities on social media result oriented recruitment and selection, continuous training needs assessment, career development practices, team building and handling grievance procedures necessitates to move in the dynamic business environment.

From the review of past studies, analytics aids an organization in developing workforce strategy linked with business strategy by improving the retention of key talent and thereby increasing the efficiency and productivity of workforce. HR analytics allowed organizations to enhance workforce efficiency with the help of gathering information, and utilizing the information making much better choices as well as procedures. HR analytics linked company's' information and individual's information to display the

effect HR has on an organization and make ways to enhance results. HR analytics offers a perspective for efficiently handling its workers to obtain company objectives quickly and efficiently.

HR analytics determined what information to model and predict; therefore, the companies could get Return on Investment (ROI) on their human capital. Analytics had been the most distinct skill experiencing the business. Therefore, Analytics was a vital concern to the organization. HR executives dealing with analytics will benefit throughout from their competitors and locate themselves along the winning aspect within the worldwide skill competitors.

To attain objectives of the study, research methodology chapter had been designed, which included objectives, hypotheses, and research design, sampling technique, data collection and research instrument. The present research examined the factors bringing out the need for human resource analytics in identified banks. It recognized the role of human resource analytics in decision-making in human resource functions. Further, it attempted to measure the effect of various types of analytics on identified human resource functions. The present study focused on two variables Human Resource Analytics and Decision Making. The determining variables taken from human resource practices were recruitment, training and development, performance management and retention. The independent variables included descriptive, predictive and prescriptive analytics. The study's dependent variable was decision-making, i.e. recruitment decision-making, training and development decision-making, performance management decision making and retention decision-making. The hypotheses were formulated based on the role of HR analytics on decision-making and the effect of HR Analytics on identified HR functions.

The responses were collected from Reserve Bank of India listed commercial banks in the Punjab region. All the respondents were senior managers of Nationalized and Private Indian bank branches in Punjab. In the Public sector, the State Bank of India, Punjab National Bank, Bank of India, Bank of Baroda and Canara Bank and the Private sector included HDFC, Axis, ICICI, Yes and Kotak Mahindra Bank, which were the top five performing banks based on net profit and maximum base of employees. Two types of

banks were considered as two strata of the population, as each type consists of homogenous firms in terms of their type. The unit of analysis for this study were the bank branches. 239 managers were taken from the Public, and 234 managers were taken from private banks to achieve the objectives. A self-structured questionnaire considering various factors was prepared, which was circulated among bank branch managers and human resource managers in twenty-two districts of Punjab to conduct further analysis. The instrument was formed with combination of question statements related to variable under study. The survey instrument was divided under four sections. To examine the current use of HR analytics, a total of 14 statements were considered. In effectiveness of human resource function; statements included related to overall performance of HR department, well defined roles and responsibilities of HR department, HR department adds value to business and preferred existing working style (Wright et al., 1998). For identified HR functions; recruitment function consists of 14 statements, training and development function consists of 14 statements, performance management consist of 12 statements and retention consists of 12 statements. The questionnaire enabled quantitative data to be collected and standardized internally, consistently and coherently.

The scaling technique used for the questionnaire development is a nominal, seven-point Likert scale type. A pilot study was conducted using a questionnaire among fifty respondents, Senior Managers from Public and Private sector banks, and managers experienced in the organization for at least two years. The questionnaire was circulated among the senior human resource managers and experts from academics. Respondents rated the statements, and further mean scores were calculated; scores more than value three was considered. The data was collected and analyzed from fifty respondents, and the extent of response variation was identified.

The researcher collected extensive primary data correctly and edited to get meaningful insights in the context of the objectives defined; this required analysis of 400 responses by utilizing instruments suitable for extracting the right information out of the available data into descriptive statements or inferences about relationships. The descriptive data of each respondent from the final database (name of bank, gender, department, designation,

qualification, experience) was imported into SPSS file. The coding template included the following sections: Current use of HR analytics (Analytics_S1 to Analytics_14); perception of decision making in HR functions (DM_S1 to DM_S4); Recruitment (Re_S1 to Re_S14); Training and Development (TnD_S1 to TnD_S14); Performance Management (PM_S1 to PM_S12) and Retention (ER_S1 to ER_S12). To test the significance of the set parameters, the researcher applied factor analysis, multiple regression analysis, structural equation modelling, averages, percentages graphs, bar diagrams and statistical package for social science (SPSS) package version 20.0 were used to analyze data and outputs interpreted in the present study.

The study's findings reveal that the majority of banks, both public and private, use human resource analytics applications. The three factors bringing out the need of HR analytics in select banks are named as 'Descriptive analytics', 'Predictive analytics' and 'Prescriptive analytics'. First, the factor-wise influence of HR analytics factors on decision making in HR functions is found to be significant. The factor 'predictive analytics' is found to be the strongest predictor of effectiveness of decision making in HR functions. Second, HR analytics effects recruitment function with components of descriptive, predictive, and prescriptive analytics in the banks. The finding reveals prescriptive analytics (0.598) is the most influencing path, followed by descriptive analytics (0.307) based on standardized coefficient. Third, HR analytics effects training and development function with components of descriptive, predictive and prescriptive analytics in bank. The finding reveals prescriptive analytics (1.011) is the most influencing path, followed by descriptive analytics (0.389) based on standardized coefficient. Fourth, HR analytics effects performance management function with components of descriptive analytics, predictive analytics and prescriptive analytics in bank. The finding reveals prescriptive analytics (1.015) is the most influencing path, followed by descriptive analytics (0.442) based on standardized coefficient. HR analytics effects retention function with components of descriptive, predictive, and prescriptive analytics in bank. The finding reveals descriptive analytics (0.409) is the most influencing path based on standardized coefficient.

The present study explored the role of HR analytics such as descriptive, predictive and prescriptive analytics, in human resource decision making. Banks relies primarily upon descriptive analytics due to the fact that key function of finance is reporting. It is suggested that banks to adopt a forward-looking approach, building insights into what may happen instead of describing what had already occurred. From the perspective of improved decision making, the study would add value to the banking and financial sector in large. The study had several implications for key stakeholders such as HR managers, HR leaders and consulting practitioners, and the CEOs, academia and policy makers.

The study contributed by developing reliable insights into unexplored research area in context of human resource decision making in banking sector in Punjab. The research findings carried substantial implications for human resource practitioners and managers working in banking industry at state and national levels.

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CHAPTER-1

Introduction

This chapter presents the research question. In later parts of this thesis, the rationale and objective of the research will be examined in greater detail. First, this chapter describes the study objectives, the research model, and the constructs. The chapter then develops the thesis by providing structure.

1.1 Background of the study

The human resource function is experiencing a paradigm change from data collection efficiency to data analysis in practice. The introduction of technology in human resource function facilitates the maintenance of objective and accurate personnel data for strategic decision-making. (Prosvirkina, 2013). Applying evidence-based management necessitates using evidence when making decisions will produce the best results. Due to market demands, the analytics field has expanded and become a crucial tool for enterprises to make strategic decisions. Data analytics mitigates the hazards associated with irrational decision-making. (Banerjee et al., 2013) The primary benefit of employing analytics in commercial decision-making is the elimination of subjectivity. With the application of exploratory statistical methodologies and data mining tools, important patterns or unidentified relationships are identified for use in making business decisions. The implementation of technology in human resource functions has a profound effect on HR practices and procedures. On average, the firms who have employed a data-driven decision-making approach are 5% more effective and earn 6% more profit than the competitors. (McAfee, 2012). Bank organizations have undergone dramatic transformations as the economy's dynamism has shifted. The significance and effectiveness of human resource practices were demonstrated by a paradigm shift in the systems, processes, and strategies of the Indian banking sector (Bhatt, 2013). Various functions and businesses increasingly rely on analytics to generate significant business outcomes. Human resources analytics have a role in recruitment, selection, training and development, succession planning, employee retention, employee engagement, and compensation and benefits. (Mishra, 2016).

With an organization's emphasis on human capital, analytics in human resources are a must for most firms. In human resource management, technology enables application

of the specialized human resource practices, hence boosting organizational performance. Human resources have fundamental functions that can be enhanced by applying analytics procedures. For the banking industry, it is of the utmost importance to conduct research emphasizing the impact of human resource analytics on human resource operations, such as employee recruitment, training and development, performance management, and employee retention.

HR analytics has become a prominent area for academic and practitioner applications. The study in HR analytics focuses on the technological and organizational enablers of HR, the descriptive, diagnostic, and prescriptive applications of HR analytics, and the employee and corporate value of HR analytics. The studies examined the evolution of HR analytics, methods, antecedents, outcomes, and success factors. The pair Marler and Boudreau (2017). In most papers, the research design was either qualitative or a combination of quantitative and qualitative methods.

Past research on the topic gives an in-depth grasp of human resource analytics, leading to experience- and subjectivity-based suggestions. With the maturation of enterprise resource systems, firms must do more with data (Deloitte, 2014). Even though analytics is the future of HR, there is a need to define components of HR analytics and undertake in-depth analyses of how analytics are implemented in HR. Additionally, the dimensions involved must be specified, and the hurdles to business adoption must be identified (Fernandez & Gallardo Gallardo, 2020). The literature on the adoption of HR analytics is scant. The research focuses on the barriers to HR analytics adoption from an individual perspective (e.g., Vargas et al., 2018) instead of organizational ones.

Literature studies comprised integrative synthesis of existing peer-reviewed literature on HR analytics, extended literature-based systematization of HR analytics ideas and investigation topics, case-based analysis, and bibliometric analysis. The field research concentrated more on new technology and intelligence capacities than analytic applications in service sector decision-making performance. The application-based studies assessed data using predictive approaches such as Warp PLS, Pearson Correlation Analysis, and Partial least square equation modeling. This study stresses the utilization of metrics and analytics for decision-making purposes.

The acquired data were examined using descriptive and inferential statistical techniques, such as Exploratory Factor Analysis, Multiple Regression, and Structural Equation Modeling.

1.2 Rationale of Study

Human capital is the differentiator between success and failure in service industries. The increased usage of big data and technological advancements created opportunities for businesses to invest in newer technologies. Human resource requires analytic application to bridge the gap between human resource activities and outcomes.

The service organizations like banking can sustain with HR Analytics that aligns people's data to make strategic decisions. Previously, the measurement of human resources was inappropriately focused, preventing the function from measuring its outcomes (Boudreau & Ramstad 2002). The present study aims to achieve the application of novel approaches affecting HR practices lacking in the financial sector. The study will find how HR Analytics improve decision-making in the banking sector of Punjab, which is one of country's extensive networks of banking facilities states. The study will examine the factors that influence the need for HR Analytics and its relationship on the four major functions of human resource management.

The study adds to how academics and industry professionals evaluate and comprehend data intelligence and analytics for effective service sector decision-making. Previous research has demonstrated that banking institutions require sophisticated, multifaceted approaches, including analyzing skill requirements, allocating available talents optimally, managing employee performance, and retaining talent (Subbarao, 2008). It has become essential to review the current HR practices affecting bank performance and reevaluate their operations in light of evolving paradigms. (Chakrabarty, 2011a, 2011b).

Applying analytics in human resource management will replicate best practices, such as gaining insight into specific recruiting channels that produce the best candidates, identifying high-potential employees, keeping employee learning in step with changing skill requirements, and facilitating succession planning to meet the productivity challenge. This study aims to contribute to the body of knowledge by reaching enlightening conclusions in HR analytics for decision-making in the banking industry.

1.3 Significance of the Study

The study's primary purpose is to probe into decision-making using human resource analytics and advance the limited academic research in the field. Research in human resource analytics adopted conceptual methodology involving the application of analytics and its impact on business. Most research has focused on high-tech firms, with little emphasis on the financial sector. The study investigates the banking industry in Punjab, India's 16th largest state economy (US\$68 billion in FY2020-21) in gross domestic product. Previous research did not explain the relationship between factors influencing the need for HR analytics and human resource decision-making.

This area has remained unexplored, thus, highlighting a gap in decision-making effectiveness with HR analytics. Many studies focused on adoption factors and implications of HR Analytics based on case studies and small sample sizes. This study investigated a large sample by a survey to collect primary data from managerial respondents of the bank for precise and justifiable results.

1.4 Application of Human Resources Analytics in Business

Through information-based prediction, analysis, and inference, human resource analytics help the organization understand what it is, what it has been, and what it will be. Human resources analytics helps an organization make personnel decisions by saving costs, identifying revenue streams, limiting risks, and implementing efficient business strategies. (Carlson, K. D., and M. J. Kavanagh, 2011) Human resources analytics illustrates the relationship between human data and crucial business outcomes. (Mondore et al 2011). Harris, Craig, and Light (2011) conducted a study in which they suggested that human resource directors must do more than utilize data to report on past performance, generate compliance reports, and complete administrative chores. Executives must use data to ask (and answer) challenging questions about how people will contribute to the organization's performance. With analytics, the human resources function executes a pragmatic strategy to assist executives in making the proper investment decisions based on effective analysis and initiatives. The objective is to evaluate the past and present to anticipate the future using data and facts. As a result, human resources may demonstrate the business benefit of their operations and boost their corporation's bottom line. The role evaluates the consequences of human capital expenditures and anticipates future needs and opportunities by collecting the correct data and using analytics to monitor

performance. Human resources analytics equips Human Resources Managers with precise predictive analytics, allowing them to identify businesses wanting a more proactive role in driving company strategy. HR analytics enables firms to gather systematically, store, and retrieve information about their people and organization to gain valuable business and efficiency insights. Human resources analytics enables human resources managers to make human capital decisions that affect business outcomes and increases human resources' participation in defining company strategy.

1.5 Conceptual Model of Study

The conceptual model of human resource analytics and predictive decision-making developed by Abdul Quddus Mohammed (2019) is the foundation for this research. This study's proposed model is based on human resource analytics, its types and decision-making in HR functions. Human resource analytics examine recruitment, training and development, performance management and retention functions. Based on the data analysis, predictions regarding recruiting, training and development, employee performance, retention can be made, and decision-making recommendations can be provided. The framework enhances research in human resource decision-making by emphasizing the application of human resource analytics to develop effective decision-making recommendations.

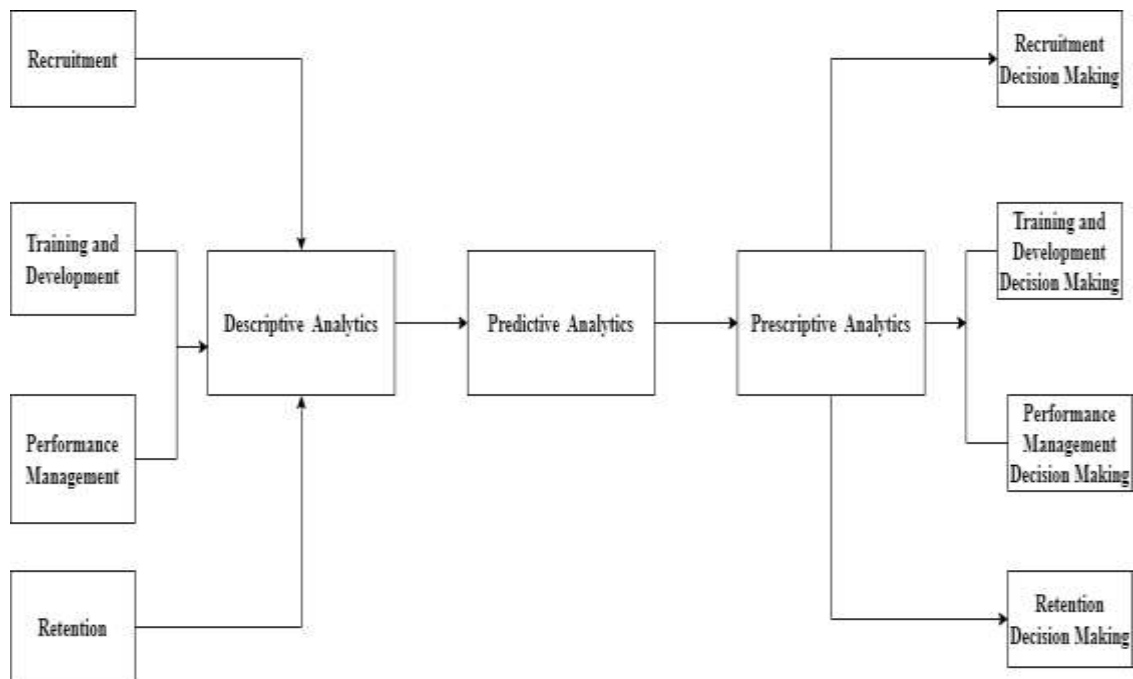


Figure 1.1: Conceptual Model

1.6 Constructs of the Study and their operational definition

1.6.1 Recruitment

Successful hiring requires identifying the right candidate with qualifications for a vacant position at the right time. Recruitment is the process by which companies identify and hire potential employees. This function aims to create a pool of job seekers leading to the recruitment of potential employees. Recruitment is a positive process as it includes the search for employees. The chances of better hiring take place with more applicants applying for a particular job.

Human resource analytics integrates information from resumes, job descriptions, references, relevant experience, and interviews with mathematical algorithms to answer questions regarding a candidate's fit for an open position. The "most qualified" candidates for a certain position can be determined through recruiting analytics.

Using analytics for recruitment requires identifying, analyzing, and simplifying relevant trends for sourcing, choosing, and hiring candidates. The data identifies and explains practices such as if new hires quit within the first three months, which suggests a mismatch between the job description and the actual job, selection problems, and poor on boarding. Important recruitment indicators include the time to hire, the cost per hire, the percentage of new hires that leave within the first year, the average number of months since the last promotion, etc.

1.6.2 Training and Development

Training and development are the educational activities conducted within a business to improve its employees' knowledge, skills, and talents. This function discovers capability gaps and fills them. Training and development are regarded as the most important aspect of human resource management since they demand quantitative data-based evaluation. For training to be practical, it must be a planned activity carried out after a comprehensive study of needs. An organization's upper management needs proof that the training function contributes favorably to the bottom line. Human resources analytics seeks to answer some of the data-driven queries posed by management to the Department of training and human resource development. Questions are raised regarding the interventions with the greatest influence on employee effectiveness, interventions focusing on a specific problem, the impact of a particular training intervention, and the training interventions with the

greatest impact on productivity. The most important training and development metrics include training costs per employee, the training effectiveness index, and training efficiency, among others.

1.6.3 Performance Management

Performance management enhances an employee's ability to effectively fulfil their duties. It tries to monitor and assess employee performance. Performance evaluation methods such as ranking, field review, and critical incidents are trait-based. Performance management is a strategic process it seeks to connect individual aspirations with group and corporate objectives. This process is connected to the most significant individual career decisions, such as pay, promotions, and layoffs. The evaluation of employees is based on benchmarks of personal characteristics that are vulnerable to criticism.

With HR analytics in performance management, HR may identify low-performance indicators and address them before they become an issue that results in employee turnover or decreased productivity and income at the enterprise level. The application of analytics to performance management enables firms to better understand what is required of their staff to increase productivity and, eventually, to improve enterprise-wide performance.

The data provided by analytics enables managers to discover performance gaps and strive to rectify them. Important performance management metrics include revenue per employee, profit per full-time employee, human capital return on investment, and absenteeism rate.

1.6.4 Retention

Retention of employees is the capacity of a business to retain its most valuable staff. Employee retention aims to satisfy both the business and the employee. Attrition inside an organization is viewed as a loss of assets. The departure of productive personnel represents a significant loss of human capital and impacts the potential for future returns. The organization invests time and resources in training and equipping new personnel. If trained employees quit the company, the corporation suffers a loss. Evaluating the causes of attrition within a company can aid in sustaining and retaining a talented workforce. Human resources analytics answer separation-related problems, such as the causes of high turnover, the aspects firms must prioritize to reduce

regrettable turnover and retain high-potential individuals, and whether organizations meet human resources requirements.

Descriptive analytics responds to "what occurred" and "what is now occurring in the organization". This is the most fundamental type of analysis involving collecting and summarizing historical data. It comprises data visualization, ad-hoc reports, dashboards, scorecards, and SQL queries. This analytics generates KPIs and metrics for usage in reports and dashboards.

Metrics and key performance indicators allow businesses to monitor their performance and trends. It enables the company to make more informed judgments. It reveals patterns in raw data, allowing management to evaluate the business's performance and potential areas for improvement. Descriptive analytics aids firms in communicating information both internally and externally. Indicators such as turnover rates, cost per recruit, and absence rates are utilized for descriptive analysis.

Predictive analytics involves predicting a company's desired business outcomes. Data mining, decision trees, pattern recognition, forecasting, root-cause analysis, and predictive modelling are involved. Predictive analytics examines a data pattern and builds a correlation to assess if a similar occurrence will occur. Beyond identifying what has occurred, the objective is to predict what will occur. It enables enterprises to be proactive and predict outcomes based on data instead of preconceptions. It assists human resource managers; for instance, predict attrition rates and the likelihood of employee success, depending on recruitment and selection processes. Predictive analytics provide solutions that effectively address talent management challenges. Prescriptive Analytics Utilizing data, prescriptive analytics determines the ideal course of action. It responds to the query on the optimal course of action. It integrates prediction and decision-making while considering the consequences of those decisions. Prescriptive analytics advises a plan of action or strategy based on knowledge of anticipated scenarios, available resources, and previous and present performance.

It aids in making immediate and long-term decisions and utilizing linear programming, simulations, mathematical modelling, and its implementation to determine the optimal alternative for achieving organizational effectiveness.

1.6.5 Human Resources Decisions

An organization takes analytical decisions which are:

Data-based decision: analytic and applied to rich data, enables an organization to more accurately define its strategy. These decisions are directed towards an individual and at a small group level. These decisions require investment in the latest analytical software. Data-informed decisions: insights to make people decisions. These decisions provide directional indications at the small group level.

Within the changing human resource landscape, decision-making is altering. Once the outdated methods for managing human resources are inadequate to maintain speed with new technology and competition, the area is at a crossroads. Human resources are transitioning from transaction to interaction, with technologies replacing the traditional relationship between stakeholders and employees. Human resource management is a crucial aspect of an organization's decision-making process. There are two types of decisions: strategic and tactical. Human Resources has become a highly specialized niche market that is no longer responsible for administering tasks linked to human resources but for achieving the organization's overall business objectives.

Historically, the nature of human resource management required decisions on several elements of personnel in addition to other human resource considerations. Organizational effectiveness is influenced by the decisions taken. Human resources executives and practitioners have encountered difficulties due to a lack of human resources data. Human resources analytics investments can have a top-to-bottom impact and be quantified, facilitating decision-making throughout the firm. Professionals in human resources strive to eliminate subjectivity from human resources-related choices to improve their quality. Data analytics is an effective weapon against the risk of inconsistent, irrational decision-making. To effectively influence HR analytics, businesses must collect data and ensure it is used for decision-making and process improvement.

Companies are increasingly aware that employee data may help them acquire and retain the finest talent; they are investing in HR analytics equipment and hiring skilled personnel to assist them in understanding and utilizing the data. Deloitte reported that its volume increased by a third to 32% in 2016, while other businesses were preparing

themselves in 2015. Human resource managers can utilize human resource analytics to tackle various problems by analyzing huge amounts of data and predicting future organizational challenges, such as talent acquisition, training and development, performance management, and employee retention. Then, managers utilize the vast amount of available data to make the best decisions to address problems and improve workplaces.

1.6.5.1 Recruitment Decision Making

A human resource manager can select the recruiting source for developing a pool of possible candidates for screening using analytical insight into recruitment. Appropriate compatibility between the candidate's knowledge, skills, attitude, and job requirements can lead to sound decision-making. Identifying a candidate's interest in the role and determining the candidate's success on the job using human resource analytics would result in effective decision-making.

1.6.5.2 Training and Development Decision Making

Analytics aims to determine which training and development interventions have the greatest influence on employee effectiveness. The analytics can evaluate the effectiveness of a training intervention and which training intervention has the greatest influence on productivity, facilitating sound decision-making.

1.6.5.3 Performance Management Decision Making

The use of analytics assists the human resource manager in determining whether an employee's performance has economic repercussions. With human resource analytics leading to decision-making, it is possible to determine employee attributes that influence customer happiness, contribution to essential company processes, and employee potential for improved performance.

1.6.5.4 Retention Decision Making

Human resource managers are aided by analytics in identifying the causes of high turnover. With human resource analytics resulting in effective decision-making, the business can identify key areas to reduce regrettable turnover, retention of high-potential personnel, the satisfaction of human resource needs, and employee loyalty.

1.7 Scope of the Study

The research covers select banking organizations operating in Punjab because it is declared a surplus state in banking facilities. The study covers a total of 22 districts in Punjab. The performance of the banking industry depends on progressive human resource practices. The present research is conducted at managerial levels deputed in both public and private bank branches and administers human resources management. Although the research covers bank branches in Punjab, the conclusions can be justifiably applied to branches nationwide.

1.8 Structure of Thesis

The remainder of the thesis comprises six chapters plus a bibliography and annexure. The first chapter briefly introduces the research and conceptual framework to the research context. Chapter Two: provides an overview of the academic and practitioner literature on Human Resources Analytics. The literature review offers a profound look at Human Resources Analytics application in Banking, sector-wise Human Resources Analytics, the reason for choosing banks for Human Resources Analytics, and the four selected functions for Human Resources Analytics. Further, it consists of parts of Human Resources Analytics and the role of Human Resources Analytics in decision-making. Chapter three: furnishes and presents the research design flowing from the gaps identified in the literature review is outlined. In Chapter Four: Organization's Experience with Human Resources Analytics, Data analysis of the present research is represented and discussed. Chapter Five: Findings and Suggestions. Chapter Six: Managerial Implications, conclusion, and Scope for future research.

Chapter-2

Review of Literature

This part of the chapter reviewed the literature published in the subject area of study to facilitate the researcher to understand the contributions and development of the topic under study. This chapter analysed the published literature on Human Resources Functions, Human Resource Analytics, and Human Resources Decision Making. The compositions provided in this chapter are- the definition of HR analytics, understanding human resource analytics, application of HR Analytics, sector-wise application of HR analytics, the reason for choosing four functions for HR analytics, Analytics in HR practices, HR analytics application in banking, HR practices in the banking sector, the role of HR Analytics in decision making and future of HR Analytics. The present study concentrated on four HRM practices- recruitment, training and development, performance management and retention. This chapter concludes by identifying gaps in the existing literature and the research problem.

2.1 Definitions of Human Resource Analytics

A combination of "talent" and "stewardship," the term "Talentship" was first used by Boudreau and Ramstad in 2003. The authors contend that human resource decision science directs and improves important choices that affect talent. According to Davenport and Harris (2006), the definition of analytics is the full use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to inform decisions and guide action. HR analytics was described by Boudreau and Ramstad (2007) as the process of logical analysis that uses business data to forecast business outcomes (Fitz-Enz, 2009). Human resource analytics is a communication tool that integrates data from multiple sources to provide a cohesive, actionable picture of the current situation and what is expected to occur. Talent supply chain optimization is achieved through various applications, ranging from fundamental human capital data to the most complex analytics. (Davenport and others, 2010) Basic reporting of HR data or metrics to predictive HR analytics was included in HR analytics. Bassi (2011)

HR analytics, or workforce analytics, integrates HR data with statistical models to anticipate future outcomes and events. HR analytics combines quantitative and qualitative data and information to give personnel management insight and decision-

making help (Handa & Garima, 2014). HR analytics entails techniques for unearthing unique human resource insights that help executives make decisions faster and more precisely. Guenole et al (2015).

Human resource analytics (HRA) is a statistical measurement and data modelling used to assess historical data and forecast future outcomes. Jain et al.,(2017). HR analytics delivered judgments based on evidence and data, prioritizing HR investments to improve business performance. HR analytics is the application of statistics and machine learning tools and techniques to enhance human resources performance by employing quantitative data, modelling, and analyzing employee-related factors.

Lawler et al. (2004) presented the most detailed description of HR analytics compared to all other definitions: HR Analytics transformed individuals' data and metrics into comprehensive and pertinent insights. The process incorporated research design but goes beyond finding and articulating essential research questions, collecting, and using appropriate data within and beyond the HR function, and increasing the analytical competencies of HR across the entire enterprise.

2.2 Understanding Human Resource Analytics

The widespread use of the Internet had altered the evolution of the human resources industry, resulting in a rise in HR analytics usage. Introducing disruptive technologies like artificial intelligence, data analytics, machine learning, and the Internet of Things had increased data-driven decision-making. Technological advances resulted in rapid growth in the industrial and service sectors and a tendency to embrace creative and effective methods. Human resource analytics evaluated several HR measures, including productivity, performance, and effectiveness. Human resource analytics aid firms of all sizes and industries in directing skill, management, and hiring decisions. Human resource analytics provided awareness of managing workers and accessing company objectives. HR analytics offered a valuable strategy for assisting administrators in creating the appropriate investments based on practical initiatives and compelling analysis. In human resource management, analytics had been discussed and utilized for years. Fitz-Enz advocated for measurement of HR actions and their impact on the business. In the late 1980s and 1990s, several studies attempted to establish a connection between HR practices and organizational success.

However, most of the research lacked empirical dynamism, was limited to detecting correlations between two variables, and could not predict future results. (Bassi, 2011).

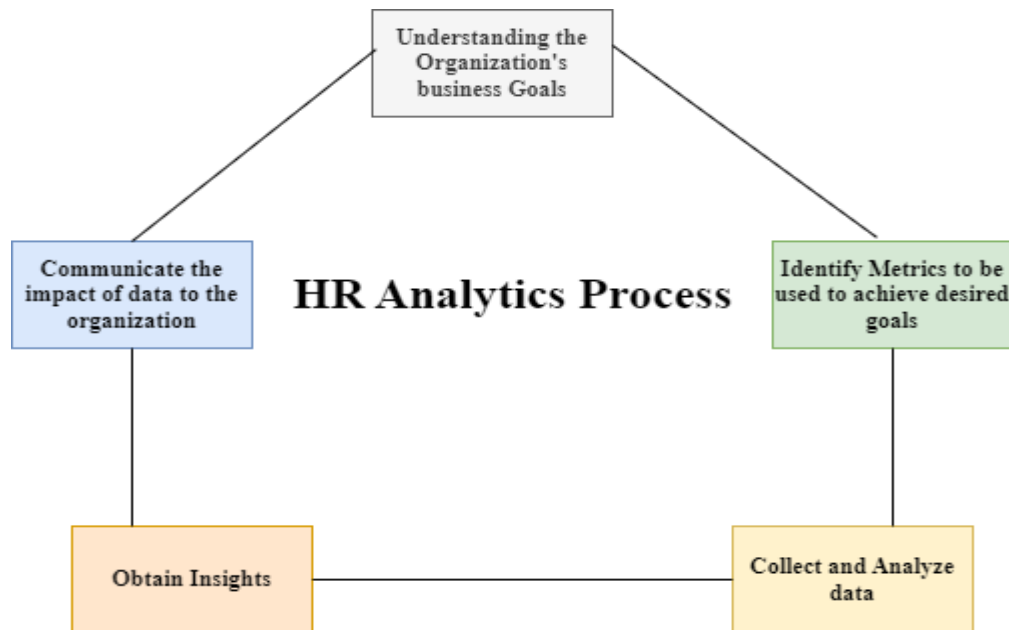


Figure 2.1: Process of HR Analytics

Studies contributing to understanding the field of Human Resource Analytics are presented in this section:

Human resource analytics is a strategy for understanding and analyzing the causal connection between organizational performance and human resource practices resulting in legitimate foundations for human capital decisions (Lawler et al.,2004). Applying analytics to human resources is not nascent; it has been in practice for decades. According to Gibbons et al. (2007), statistics were utilized to monitor employee contributions, employee benefits, production downtime, and worker productivity. According to Boudreau et al. (2007), analytics is a value driver in human resource management (HRM) because it enabled the systematic analysis of complex data, which had the potential to tackle numerous organizational difficulties.

Human resource roles had been enhanced by combining access to metrics and the automation of administrative functions, enabling human resources to contribute significantly at a strategic level (Dery K et al.2009). According to Harris et al. (2011), academics and consultants in human resources wrestled with talent judgments and attempted to reposition their departments toward business-relevant

measurements. Executives could use analytic tools to link human capital investments to a company's return on financial capital.

HR leaders may define the organization's destiny by managing talent and directing initiatives toward the enterprise's long-term goals. Analytics was defined by Kiron et al. (2011) as the use of data and related insights generated by statistical, contextual, quantitative, predictive, or cognitive kinds to drive fact-based planning, management, execution, decisions, learning, and measurement.

HR Analytics is a significant advancement, and companies are concentrating on applying an analytical strategy that might systematically influence their company efficiency. In their study, Hoffman, Lesser, and Ring (2012) explained that workforce analytics deals with individuals as widgets. Rouse M (2012) indicated that HR analytics offers a perspective for efficiently handling its workers to obtain company objectives quickly and efficiently. HR analytics allows determining what information to model and predicting features so companies can get a return on investment (ROI) on their human capital. The experts considered that businesses that use HR Analytics probably have the most interested staff members and flourish via tricky occasions. The analysis revealed that company executives and HR experts create data-driven choices using the strength of human resource analytics, and businesses are utilizing predictive analytics to direct succeeding choices. Companies that constantly use analytics to make fact-based choices can regulate their strategies faster than their competition. Organizations realized that analytics empowers supervisors to make highly effective, fact-based decisions. It provides a regular practice for obtaining and analyzing considerable amounts of information. It makes it possible for HR experts to get awareness directly into various business tasks to operate much better. Gartner (2012) explored human resource analytics as a sophisticated group of information evaluation programs, metrics for extensive workforce general performance measurement, and enhancement. Johnson and Dulebohn (2012) contended that HR providers must supply interest in the demand for HR metrics. They determine HR metrics as an accountability application that allows HR performance evaluation.

HR analytics has been revolutionizing companies and businesses that produced investments to transform their skills and technology to become more analytically able, attaining considerable benefits around their competition. Nick Holley (2013)

studied big data and human resources. Within this analysis, they evaluated the potential of human resource analytics would transform human resources. The study discovered that secret to effective HR analytics initiatives was driving activity from company issues wherein awareness obtained from HR analytics operate a vehicle company efficiently. It was discovered that under twenty five (25%) of CHRO (Chief Human Resource Officer) utilized analytics to create upcoming workforce choices, just six (6%) of HR division thought they happen to be "excellent" in analytics and over sixty (60%) sensed they had been bad found HR analytics as well as eighty five (85%) of respondents mentioned which the HR team of theirs didn't succeed delivering predictive and insightful analytics. Josh Bersin (2013) in their study surveyed 436 North American Companies. The analysis exposed that superior skill analytics can help attain much better skills within the terminology of leadership pipelines, skill expense minimization, effectiveness profits, and skill mobility - shifting the appropriate individuals within the correct tasks. Thirty (30%) had been utilizing HR analytics for choice generating, and fifteen (15%) companies considered that their HR teams have the powerful authority of skill analytics. The majority of companies searched for a roadmap to enhance their capabilities of theirs. In their study, Ghosh et al. (2013) identified the elements that assist in distinguishing between employees who intend to quit and those who intend to remain. A systematic questionnaire encompassing multiple employee retention criteria was sent randomly to 100 employees. The study revealed that employees with a high level of affective and normative commitment to the firm would have a lower intention to leave, demonstrating the necessity to strengthen employee commitment. Discriminant analysis can assist a company in being proactive and in establishing its retention strategy.

(Kong et al. (2013) investigated the influence of HR practices in generating knowledge and learning abilities for innovation in the Indian IT industry. To achieve objectives, semi-structured in-depth interviews were conducted with senior IT service provider executives in India. The results indicated that developing knowledge and learning skills is crucial to talent management architecture. Internet service providers were compelled to develop HR strategies to manage a vast pool of qualified IT professionals and ensure that their expertise remains industry-relevant. Human resource analytics accommodates the shift in emphasis of the human

resources department from employee retention to employee pleasure and competitive advantage potential maximization (Fitz-Enz, 2014). HR professionals and experts, found that analytics was a typical road to company worth. Many companies have been altering their choice-generating, running and approaches utilizing HR analytics and appearing to analytics to get a benefit and boost their performance. The study found that companies produce far better utilization of information, the road to value with analytics. Fitz-Enz (2014) reported particular suspicion above the importance of the initiatives that must accompany the dramatic and recent increase in the acceptance of HR analytics. HR analytics should not be limited to measuring administrative efficacy

Implementing big data in the human resource function should capture the strategic link between human capital and profitability, deciding the HR function's ability to boost employees' skills and knowledge to establish a competitive advantage and improve firm performance. (Jackson, Schuler, & Jiang, 2014).

Business executives are adopting workforce analytics as a fundamental approach to influencing monetary outcomes. The primary goal of utilizing workforce analytics had been cost saving. In a report on human capital analytics, Jack Phillips et al. (2014) offered several insights into more than a hundred companies with committed assets to human capital analytics. The analysis surveyed 2,532 companies and HR frontrunners in ninety-four nations worldwide. Within this analysis, they found that HR was changing into a data-driven feature. Forty-five (45%) of the businesses ranked themselves as "not ready," analyzing the willingness of their deep HR analytics, and just seven (7%) of big companies ranked their organizations of theirs as getting "strong" HR information analytics abilities.

Businesses suggested they recognized the benefits of creating their HR and skill analytics features and disclosed multiple spaces inside their present capabilities and readiness. According to study conducted by Kiron et al., (2014) the Information and Analytics Global Executive Research and Study surveyed using the analytics on the subsequent fitness level via 2,037 respondents. A great bulk of respondents felt their companies to become performing much more with analytics. Bersin (2015) examined more than 3,300 firms and HR leaders in 106 positions and determined that analytics is the most distinctive skill affecting their business. These studies have investigated the leading fashion with worldwide human capital and choose the

ability spaces related to every direction. They have also provided useful insights to assist the organization in dealing with its issues. For an outcome, people's analytics given the largest total ability gap for companies. Many companies display the importance of analytics, a brand new racing to become competitive by comprehending each element of the workforce. In research, Josh Bersin (2015) mentioned that an organization with recognized skill analytics functionality permits HR to use innovative statistical versions or predictive analytics. Analytics teams can look at the usefulness of various recruiting resources and the quality of hires. They propose that HR teams must motivate skill analytics for much better functionality for their organization. HR must create a skill analytics application that will help recognize the company challenges human resources to confront. Companies may be more proficiently handled, and overall performance raised by applying HR Analytics.

The study was done through the Center for Advanced Human Resource Studies, using the goal of making an introduction along with the analysis issue split into four distinct areas, Value, Application, Systems, and Structures. This particular analysis's primary themes and goals were that companies did not consider HR Analytics an essential portion of the organization's human resources within 2015.

HR Analytics is active in proving itself with the bigger companies but will be more critical for enterprises wearing 2025 because HR Analytics is realized and can certainly concentrate. CIPD (2015), in their article, examined fads in HR information compilation and evaluation and investigated considerable obstacles to the setup of HR information analytics and measurement via extensive professional interviews. This particular analysis looked a lot more carefully at how companies have used HR and skill analytics inside their companies. A seven-day online survey was conducted and then gathered hundred five replies through a blind test that solely consisted of respondents that employed HR Analytics techniques inside North America. The statement aided small business proprietors and HR experts in figuring out how analytics and data can strengthen a business's selection procedure. They discovered that many more owners of HR analytics applications than non-users rate their overall performance on typical HR methods.

In research, Mark Huselid (2015) examined a crucial action, i.e., to develop and implement plans of analytics and workforce metrics handling the various company concerns. HR and a series of executives must be ready to cultivate extensive insights into how the workforce plays a role in their strategy being successful.

Companies have to deal with their workforce smartly. Implementing and developing HR operations as well as workforce scorecards assists HR administrators in keeping themselves responsible for essentially the highest priced aid of all of the tight. Using analytical resources allows for calculating the effect of skill on organizational results. This survey discovered that most companies have begun using individual analytics. It was realized that information and analytics are crucial to fixing most issues in recruitment and learning, engagement, engagement and leadership. Rasmussen and Ulrich (2015) explained that HR analytics had been a climbing pattern of HRM in the last several years and a solution to the difficulties dealing with HR. Information analytics aims to transform huge, complicated masses of information into expertise. It supports HRM decision-making by generating more correct and data-driven conclusions and forecasting the long term. Human resources must be a decision-oriented feature that produces valuation for the company to accomplish the strategic function.

Jac Fitz-ENZ stated in his book that human resources need to learn to speak qualitatively and objectively to express the activity and value added by the function. Human resource analytics enables the department to make decisions based on empirical evidence instead of hunches. Human resource analytics facilitates workforce decisions by lowering costs, identifying new revenue streams, removing risks, and implementing practical business strategies. It emphasizes the direct connection between personal data and quantifiable business outcomes. Human resource analytics is carefully identifying and quantifying a company's people owners to make better decisions (Van et al., 2016). Individual supervisors and teams were able to gain insight into the human resource component within their firm, enabling them to undertake an evaluation of the organization. Human resource analytics is the application of machine learning tools and techniques to analyze employee-related information to enhance corporate performance as companies leapfrog technological innovation. It assists human resource practitioners in making data-driven decisions to attract, manage, and retain workers for the organization's

overall profitability. Thanks to the analytical tools and methods available.

An organization's human resource division has many people-related details that may be utilized to comprehend the company's present makeup, risk, and performance. Human resource analytics operates through different levels, such as strategic and operational levels. It provides a mechanism for rapidly and successfully connecting employee and organizational objectives. The future of human resource activities is determined by predictive analytics, which assists management in making decisions that minimize risk and maximize return on investment. It allows human resource managers to be more strategic in determining whether there is enough availability of resources and the right skills in the team. Bersin (2016), in their research, reported that analytics was a vital concern of the organization. Many companies assume they are succeeding within analytics. They discovered that human resource executives dealing with personal analytics would benefit from their opposition and locate themselves along the winning aspect within the worldwide skill competitors.

HR was confronted with a golden chance to link the HR analytics operating systems with SaaS-dependent human capital managing wedge. Thus enabling HR features to understand complicated details more proficiently along with higher confidence and accuracy. HR analytics will offer tough evidence-based choice-producing to the HR group & provide invaluable company advantages. The creation of essential HR analytics can also be placed to transform the standard ways and view inside HR.

Lawrence and Angrave (2016) discussed the transformative opportunity of human resource analytics. Human resource analytics ensure the potential future of human resources being a strategic feature while changing the organizational functionality of the superior. The research outcomes may subsequently be utilized to understand human resources and improve significant daily metrics, dashboards, and measures within traditional HRIS analytics bundles. In their research, HR analytics assist in directing skills, managing and getting choices for companies of sizes and in all industries. Most companies work with analytics and metrics in human resources to figure out how they recruit, maintain, and compensate their workers. That is crucial as it enables businesses to gather and evaluate information that will boost revenues by more effectively comprehending and focusing on clients.

Witte. L (2016) addressed the problems of reasons for which businesses implement human resource analytics. Many companies anticipated HR analytics to become

helpful within the context of HR changing right into a strategic partner. Whether or not results with HR analytics depend on specific contextual elements. The research discovered that organizations implemented HR analytics to boost fact-based choice generation. The staff followed a phased method for achieving particular objectives that aided them in quickly identifying problems associated with the workforce profile, demographics, and general performance control—they built-in non-Oracle and PeopleSoft information energy sources for effectively deploying sophisticated dash panel reporting and evaluation. The HR professional struck their small setup schedule using Oracle HR Analytics remedy and a robust setup strategy. Techno was dealing with a skill managing issue when it came to using outdated methodologies and tasks in HR. The organization found organization charts with what organizational succession planning and management described. The latest HR capabilities have the HR Analytics features required to transfer a data-driven HR feature. HR analysts need to have a top-down perspective of the information and put it on key company problems. Of those surveyed, 37% declared that HR analytics software programs aided them in creating much better employment choices, with nine % rating it "excellent." or "very good". HR analytics offers a tangible website link between organizational performance and people strategy. HR analytics is considered the new face of human resource management with the potential to deliver higher productivity (Deloitte, 2017). HR analytics is more credible as it provides statistically valid data and evidence to create new strategies while implementing existing HR strategies and other measures (Mohammed, 2019). HR analytics allow decision-makers to make evidence-based and objective decisions and provides worker's opportunities for personal and professional growth (Pessach et al., 2020). The major areas of research in human resource analytics included the awareness and comprehension of HRA, human resource analytics softwares and applications as well as barriers to adoption (Chhetri S. D et al., 2023)

Table 2.1: Keywords used for HR analytics from literature (chronological order)

S.No.	Keywords in definition	Outcomes	Authored by
1	Application of methodology and integrative process	Quality of decisions regarding personnel and enhancement of organizational performance	Bassi, 2011
2	Quantitative and Qualitative data	Decision making support	Handa et al.,2014
3	Multi-disciplinary approach	Evidence-based human and organizational decisions	Rasmussen & Ulrich, 2015
4	Identification and quantification of human motivating factors	Better decision making	Van den Heuvel, 2016
5	The causal relationship, HR practices and Organizational performance outcomes, statistical techniques and experimental approaches	Human capital decisions	Reddy et al.,2017
6	Statistical tools, measures, and procedures	HRM strategies and practices	Mohammed ,2019
7	Evidence-based, Predictive communication tool	Decision-making with logic and least probability of errors	Jain. P. et al, 2020

2.3 Functions of Human Resource Analytics

Lawler et al. (2004) examined how analytics captured impact. They stated that organizational competency needs the development of skills and data to accurately analyze the connection between HR policies and practices and organizational success.

Long-term analytic capabilities must reside within HR and become a fundamental HR competency.

According to Levenson, Boudreau, and Lawler (2005), HR analytics transforms data and measurements into insights that may be implemented. It goes beyond identifying and formulating significant issues utilizing statistics and research methodology.

Human resource analytics goes beyond data collecting and dashboard reporting. It is a methodical technique for using data, organizing it, and reporting the results. Analytics provides significant insights that may be applied to business decisions beyond measurements. HR analytics strives to offer a firm a competitive advantage by analyzing human resource-related factors. HR analytics gives evidence-based direction on achieving people-centric company expansion (Mondore et al., 2011). Rouse (2012) states that HR analytics determines general and specialized hiring decisions, identifies the human requirements for new positions, analyses and predicts existing and future technical requirements, and enhances recruiting techniques. HR analytics provides a corporation with insights for efficiently and successfully managing personnel to fulfil business objectives (Davenport et al., 2010; Ghosh, 2013). Human resource analytics affects the effective implementation of company strategy (Zang and Ye (2015))

King G. K (2016) used a case study approach to illustrate how quantitative tools positively influence the management and development of human resources. Factors that supported the need for analytics included administrative support, accessibility of data, determination of internal conditions, outsourcing to gather talent and using the results of analysis; with the help of these factors, an organization can position itself as successful human resources through the use of data analytics. In their study (Fred M.O et al., 2016) recommended using analytics in human resources to forecast up to 80 per cent of employee turnover. HR analytics investigated the leadership and management abilities required by all stakeholders in a company and determined the extent to which new technical and managerial knowledge can be adopted. HR analytics results in predictive action, in which firms anticipate employee preferences and behaviours and alter HR procedures to retain valuable personnel.

Minbaeva et al. (2017) stated that establishing analytic capabilities inside an organization necessitated dealing with three dimensions: data quality, analytic capabilities, and strategic action ability. The three levels needed to be undertaken are individual, process, and structure.

Sharma (2017) stated that employees are a significant investment in organizations because they can positively impact organizational effectiveness. An organization applies HR analytics to demonstrate the benefits of talented employees more significantly than the costs. HR Analytics is the systematic identification and quantification of human drivers for business results to make better decisions.

Van den Heuvel S. et al. (2017) studied the application, value, structure, and system support of Human Resource Analytics in 2025 using a sample of 20 Human Resource Analytics practitioners from 11 big Dutch enterprises. The study's findings indicated that the evolution of HR analytics would be characterized by integrating data and IT infrastructure across disciplines and organizations. Ghosh et al. (2018), in their study, identified employees in Indian public-sector banks who felt that the training function was not systematically administered and considered it as more reactive to what competitors are doing. The study found that top managers must invest in staff development programs directly connected with employees' turnover intentions and job satisfaction. Organizations use human resource analytics to manage key employee turnover, significantly impacting business performance. HR analytics is also used to address other strategic HR issues. Organizations utilize HR analytics to obtain a competitive advantage, resolve HR-related issues, and enhance organizational performance (Tomar & Gaur, 2020).

2.4 Applications of HR Analytics

Harris et al. (2011) claimed that analytical approaches assist executives in linking human capital inputs to financial capital outcomes. Consequently, HR professionals actively shape the organization's future by managing necessary talent and creating initiatives to meet the business's long-term needs. Kong et al. (2013) examined the role of HR practices in developing competencies for innovation in the Indian IT sector. The study design and in-depth interviews with top executives of ITSPs in India were done to meet the research goals. The findings demonstrated that developing knowledge and learning capacity is a crucial element of talent management.

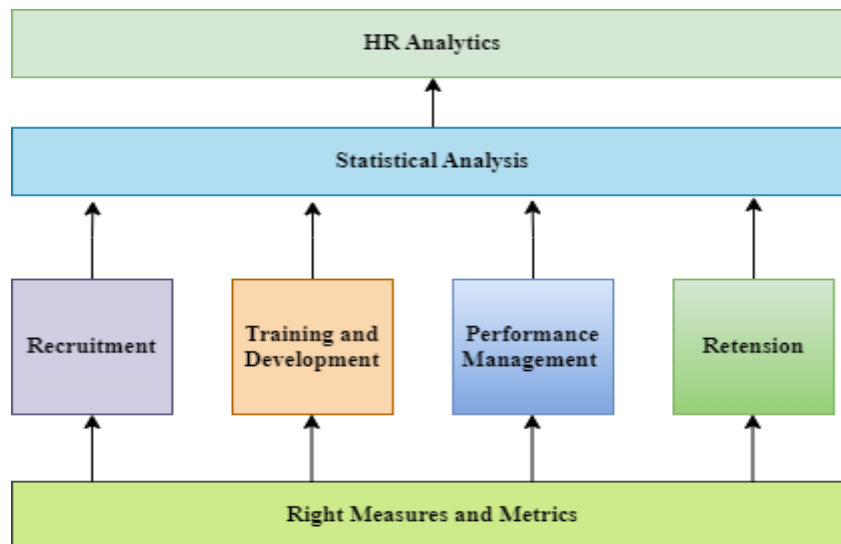


Figure 2.2: Application of Analytics

Organizations must establish human resource strategies to manage a vast pool of specialized IT employees and to ensure their expertise remains relevant in the industry. Ghosh et al. (2013) identified the elements that distinguish employees who intend to quit the organization from those who intend to stay. The study revealed that the likelihood of employees with a high affective and normative commitment to the company having a low intention to depart must be increased among workers. An organization's ability to be proactive due to discriminant analysis can aid in designing its retention strategy. Soumyasanto (2015) analyzed how HR analytics becomes indispensable for an organization's HR.

Analytics offered companies insights for dealing with workers better for company objectives to be attained efficiently and quickly. HR analytics constitutes more than simply gathering information on personnel efficiency; it offers awareness directly into every approach by gathering information and utilizing it to create related choices about enhancing procedures. Numerous companies search for analytics in HR, not only for individuals but also for tasks including recruitment, general performance management, and appraisal. HR analytics allows executives to boost organizational functionality with high-quality skill-associated choices, realize the elements which affect worker pleasure and efficiency, and figure out crucial functionality signs of a person over the company. Human resources analytics began as an administrative endeavor.

It gradually evolved to provide advanced diagnostic and predictive capabilities to improve employee engagement and retention and generate benefits for the entire organization via digitally powered analytics solutions. (Deloitte, 2017) HR analytics embraced logical and systematic ways of analyzing and visualizing HR-related data to give company managers the insightful data necessary to govern workers for organizational success. (Van den Heuvel & Bondarouk, 2017). Advanced analytics models and algorithms enable many sources of user-generated and user-related data to create dashboards that provide HR and project managers with real-time, quantitative, objective, and graphical data regarding their resources. The progression from "descriptive and diagnostic" to "prescriptive and predictive" HR intelligence is enabled by the development of technology and analytical capabilities. The study conducted by Loscher J. G et al., (2023) found three forms of accountability in human resource management that resulted as HR analytics implementation, augmentation of HR practices, and HRM improvement in organizations HR analytics has influence on organization management wherein it was statistically confirmed that adoption of technology acted as mediating factor of HR competencies to HR analytics. Penpokai et al., (2023). Based on the qualitative study 17 experts in HR analytics, the study conducted by Wirges F et al., (2023) found that a shift to more process-oriented perspective on HR analytics was required.

2.5 Sector-wise application of Human Resource Analytics

Boudreau & Ramstad (2004) defined analytics as identifying and formulating essential questions, collecting and utilizing data from within and beyond the HR function, and expanding HR's analytical skills. Dooren (2012), as cited in Lochab et al., (2018), defines human resource analytics as a strategy for comprehending and assessing HR practices that influence corporate performance outcomes such as customer happiness, sales, and profit. The methodology provides credible and dependable foundations for human capital decisions that affect corporate strategy and performance. Due to the creation of a database to evaluate employee-related data, such as learning management systems, employee development, and employee engagement analytical tools, the health industry has seen a dramatic improvement. Other components included recruitment, talent management, the learning process, benefits and pay, and succession planning. The application of modern data mining

and business analysis tools to the HR industry was investigated by Vihari and Rao (2013). Analytics is essential to the organization's long-term performance (Fred and Kinange 2015). Numerous engineering, science, and computer science areas can interact with analytics. According to (Jain and Nagar 2015) combining qualitative and quantitative data offers valuable insights for managerial decision-making. HR analytics developed a process to improve individual and organizational performance, according to Kirtane (2015). The pillars of HR analytics are analytics and statistical instruments. In their evidence-based Human Resources (EBHR) study, Reddy and Lakshmikeerthi (2017) blended critical thinking with the best scientific evidence and business knowledge. It employs data, analysis, and research to establish the connection between people management practices, company outcomes, profitability, customer satisfaction, and quality.

Kiran (2018) defined HR Analytics as a data-driven methodology that resolves business issues by generating new insights from current data. Combining software, technology, and approaches that apply statistical models to work-related data to enable corporate leaders to enhance human resource management led to intelligent decision-making. Jabir et al., (2019) analyzed HR Analytics as the study and analysis of how and why things occur. It generates warnings for the best action and investigations of the best and worst possible outcomes based on data analysis. The development of a sustainable company is facilitated by HR analytical practice's balancing of economic, social, and environmental factors. (Kirtane 2015 AT&T, Google, and Oracle use analytics to discover people with exceptional performance. Ben-Gal (2019) explained that HR analytics has multiple functions. They are utilized to:

- a. Gather and preserve data in a meaningful manner for forecasting short-term and long-term trends of supply and demand of employees in different occupations and industries.
- b. Assist global organizations in making decisions related to optimal acquisition.
- c. Develop and retain human capital.
- d. Provide insight to an organization for managing employees effectively to achieve business goals efficiently and quickly.
- e. Positively influence the implementation of human capital management systems.

According to Ben-Gal (2019), the primary goal of HR analytics is to increase organizational sustainability by analyzing acquired data using analytical methodologies and making intelligent HR-related decisions. This will enable enterprises to achieve their objectives swiftly and effectively Bhattacharyya (2017); Kirtane (2015); Kiran et al., (2018); Reena et al., (2019). The E-commerce sector manages the supply chain by identifying efficient suppliers, perfecting sales, arranging delivery orders, and controlling expenses. The industry employs analytics to estimate the demand for a commodity and fix its price to prevent losses. In addition, Analytics is utilized in optimization-related fields, such as inventory management, production, sourcing, etc. For public sector organizations the factors data management, capabilities of staff are the necessary conditions for introducing HR analytics in public organizations. Cho et al., (2023). The study found importance of metrics such as cost-to-hire in recruitment leading to effective decision-making in start-ups. Varma et al., (2023)

2.6 Reason for choosing human resource functions

Recruitment is crucial for human resource operations. Training and development promote employee performance and personnel competency to fulfill corporate objectives. Human resource professionals can approach measuring human capital. The three dimensions of quantifying human capital are the efficiency of the HR function, the efficacy of people processes, and the measurement of impact or return on investment. Muscalu et al., (2014) outlined and described the processes required to assess the strategic function of human resources. Strategic human resource management is necessary for growing firms or, more incredible speed.

Kale (2022) researched HR analytics and its impact on Organization performance in the context of human resource functions.

2.7 Application of analytics in human resource practices

HR analytics aligns employee data and technology for measuring human resources functions such as recruitment, employee performance, engagement and remuneration. Analytics is data-driven; it uses analysis and interprets the outcome of churned data. Changes in technology, pooled with a shift in industries' dynamic forces, transformed the role of human resources into an agile one. HR function plays a wide variety of

parts in the success of organizations. The main focus of the HR function is on framing an efficient workforce so that organization and employees can attain their goals.

Studies highlighting the application of analytics in human resources practices are discussed in this section:

Lawler et al. (2004) sought to assess the extent to which analytics capture the impact of human resources on a business. According to the findings, firms collected the knowledge and data necessary to determine the relationship between human resources policies and practices and organizational performance. Gibbons and Woock (2007) found that statistics have been utilized to track employee contributions, employee benefits, industrial downtime, and worker productivity. Using HR Analytics to determine what employees value and utilizing that data to develop a retention rate-improving methodology, the reason employees remain with the firm was determined. Most prominent companies in the United States implemented a human resource information system that generated massive quantities of valuable employee data. Human capital analytics aims to produce predictive or leading business indicators to help company leaders' strategic planning and decision-making.

The application of HR Analytics is considered a rung on the ladder that allows companies to anticipate employees' preferences and future actions and modify HR practices to retain valuable employees. Diverse analytic methodologies enable HR practitioners to link workforce investments to a company's human capital returns and actively affect the future of their organization by managing people and guiding programs toward its long-term requirements. Using measures such as revenue per employee, average full-time wage, and overtime rates, human resource managers can assess the impact of pay management on their firm.

Sysco Corp, a Houston-based wholesale food distributor, intended to modify its compensation system for hourly-paid employees because the old compensation system model did not improve profitability. Sysco restructured its compensation structure from hourly pay to activity-based compensation. The new design reduces errors, increases employee happiness, enhances employee retention, and decreases delivery time and costs. With the analytics-based compensation system, job satisfaction and productivity increased, employee retention rates increased by 8%, and sales expenses decreased.

In their study, Schneider (2006) & Boudreau et al. (2007) underlined that human resources (HR) must reinvent itself as a function and concentrate on offering services to support crucial talent-related business choices. In their study, Ranjan J. et al. (2008) underlined the importance of data mining in human resource management systems to a company's competitive position and organizational decision-making. Therefore, HRMS must be concerned with quantitative data. The results demonstrated that data mining improves the quality of decision-making and increases performance, contributing to a competitive advantage. Davenport et al. (2010) produced a helpful typology of analytics that illustrates the various uses an organization may make of talent analytics, such as individual-level performance and enterprise-level statistics, as well as real-time deployment of talent in response to rapidly changing demands. The value of analytics rests in determining which activities influence corporate performance most. In their study, Bassi (2011) said that human resource analytics spans from fundamental reporting of Human Resource management data to predictive HR.

Forecasting, assessing the effects of a policy change, and analyzing "what-if" scenarios are all elements of analytics in human resources. Harris et al. (2011) claimed that analytical approaches assist executives in linking human capital inputs to financial capital outcomes. Human resource professionals actively shape an organization's future by managing critical personnel and designing initiatives to meet long-term business needs. HR Analytics targets essential workforce metrics, linking workforce strategy, business goals, and results. As a result, HR can now participate in and influence business and workforce strategy decisions by identifying cost savings opportunities, enhancing key talent retention, and increasing worker productivity and efficiency. (Higgins J et al., 2011). Schalfke et al. (2013) defined performance management analytics as the broad application of data and analytical techniques to control key performance drivers and enhance organizational performance. Human resource analytics can be applied to the following human resource management functions: employment, training, development, pay, performance evaluation, talent management/succession planning, and separation. The methodology for implementing human resources analytics within an organization included determining the objectives of human resources analytics, data collection and review of human resources metrics, decision-making phase, and change of decisions. IBM Smarter Workforce

investigated the factors associated with the best and worst company performance; results revealed that employees who received forty (40) hours of training were more likely to meet their project-related objectives than employees who received less than thirty (30) hours of training. Employees' performance can be evaluated based on quality, quantity, and efficiency. (Kapoor & Kabra, 2016). Metrics for measuring performance consider whether the organization desires employees' performance, activities, and conduct. Hewlett-Packard et al. utilized HR analytics to anticipate employee turnover owing to talent shortages; thus, with five years of people data and hypotheses, it was determined that most characteristics were connected with attrition. Employers with job changes, responsibility due to promotion or lateral movement, resulting in fluctuating performance, and increased turnover were cited as causes. (Soundararajan, 2016). Sears, Inc. evaluated the effect of employee engagement on store performance by constructing a model with complete performance indicators on the employee-customer profit chain. The firm collected 1 million data points and discovered that a 5-point improvement in employee attitude linked to a 1.3-point increase in customer satisfaction and a 0.5% increase in revenue growth. The results revealed that employee work-life balance, benefits, work environment, and employee relationships are significant determinants of employee engagement. (Soundararajan, 2016). Fred M.O. et al., (2016) recommended the judicious application of analytics in human resources, which can assist in predicting around 80% of employee turnover. It is necessary to conduct research in human resources analytics to study the leadership and management abilities required by all organizational stakeholders and determine the extent to which new technical and managerial knowledge may be used. Pyne et al., (2016) did a study on HR analytics that aided in anticipating employee turnover in advance and offered ample time to examine alternative resources or acquire new workers to avoid delays in project execution. The talent acquisition process must be effective based on measurements and statistics. Soundararajan et al., (2016) discovered that HR analytics improves higher education organizations' organizational performance and efficiency. The primary responsibilities of HR analytics are succession planning, performance evaluation, training, development, compensation management, health and safety management, disciplinary management, and labor relations. Utilizing HR analytics for these fundamental tasks is useful. Sharma et al. (2017) examined the influence of human resource analytics on willingness.

The paper provided a conceptual framework and propositions in Human Resource Analytics and Performance Management. The results suggest that the application of HR Analytics will have a negative relationship with subjectivity bias in the performance evaluation (PA) system, hence increasing employee motivation to enhance performance. In her research, Maryam Ghasemaghaei (2019) examined the impact of data analytics usage on a company's decision quality and the function of data analytics competency. The survey of 133 U.S.-based companies revealed that data analytics tools increase knowledge transfer within companies, with data analytics competency having no moderating effect.

Table 2.2: Metrics for measurement of HR functions

Recruitment	Training and Development	Performance Management	Retention
Updated database	Quality improvement post training	Personnel development plans by function	Average years of experience in branch
Difficulty of recruitment	Effectiveness of the training program	Education level of staff	System to predict involuntary turnover
Speed of hiring	Improvement in post training	Competency level of each branch	Annual turnover of employees
Cost of recruitment	Competency development plans	Staff competencies related with business goals	Initiatives to retain knowledge of staff
External employee	Participant satisfaction level	Revenue per employee	Average length of service
Adherence to ethical code	Annual training hours	Effectiveness of performance management	System to predict voluntary turnover
Vacancy notification	Identification of skill gap per year	Satisfaction of new hires	The average length of service by function
Internal hiring	Tracking learner activity	Total promotions over total transfers	Staff turnover compared with market
Hiring as per	Misconduct due to	Performance to	Employee turnover of

organizational roles	inadequate training	business goals	best performers
Time to recruit	Expenditure per employee		System to assess turnover
External hiring rate	Training as a proportion of payroll		Average retirement age in branch
First-year turnover	Training as a percentage of revenue		The average length of service by region
	Training as a proportion of profit		

2.8 Human resource practices in the banking sector

Due to the nature of the banking industry, human resource management is deemed crucial for banks. Human resource in banks controls complicated financial resources and a greater scope of economic threats Sehrawat et al., (2019). Human resource management and risk management are two significant difficulties for banks. Human capital and risk management determine the performance of the banking industry. Effective risk management is impossible without competent personnel. Banking is and always has been a people's business. Banks are required to distinguish themselves by carving out niches, particularly in a highly competitive environment.

Human resource practices are organizational actions aimed at managing the pool of human resources and ensuring the optimal usage of resources to achieve corporate objectives (Tiwari and Saxena, 2012). Human resource practices are crucial for efficient and successful banking operations, developing new products, and improving customer service. (Haines et al., (2013).

Studies highlighting drawbacks and challenges that banks face regarding human resource practices are discussed in this section:

In banking studies, the emphasis has been on analyzing quantitative performance aspects and less on qualitative ones. According to Mellacheruvu and Krishnamacharyulu (2008), recruiting at public sector banks was insufficient, and the staff was scarce to meet the institutions' needs. In these banks, training had been a neglected function. In addition, they discovered that the rigidity of the system of rewards and promotion had no correlation with the performance of employees and

that banks compensated their staff less than other businesses, which led to retention and succession planning issues in the banks. They also proposed that banks be granted the liberty to recruit and promote deserving personnel more quickly.

According to Selvaraj et al. (2009) research, private banks were more effective than public sector banks regarding human resource management techniques, customer focus, and top management commitment. Nevertheless, public and private sector banks provide employees with various compensation structures, working conditions, technology, career opportunities, and job security. Karthikeyan K et al. (2010) found that training approaches vary little between public and commercial banks in South India. Therefore, when measuring the effectiveness of training, employees' attitudes toward training inputs, the quality of training programs, and their application on the job must be examined to ensure employee satisfaction.

In their study, Zulfqar and Bowra (2011) found that employees perceive a positive relationship between HR practices and employee performance. Banks must acknowledge that HR practices can influence employee performance and, consequently, the bank's private or public performance. Researchers have recognized numerous HR organizational strategies as significant performance-influencing factors. Bowra Sharif (2012) investigated the nature and relationship between employee perceptions of performance and human resource procedures in Pakistan's banking industry in her study. Multiple regression analysis and Spearman's correlation matrix determine the nature and relationship. Positive and substantial results correlated employee views of performance and HR practices. This report also includes suggestions for the banking industry's top management to reform or amend their HR policies and implement employee performance-enhancing processes. Due to a massive number of retirees, Chakrabarty (2011) forecasted in the Reserve Bank of India's (RBI) monthly bulletin that Nationalized Banks will suffer a "retirement decade" from 2010 to 2020. Due to the difficulty of selecting qualified individuals to work in rural areas, Financial Institutions, Insurance, Telecom, and other companies with a fast growth trajectory and a need for skilled workers will target the same limited talent pool. Human resource methods can differentiate banks from other companies in the same industry; there was pressure on banks to tighten and optimize their human resource operations to improve their overall management effectiveness. In the proposed improvements to human resources processes, emphasis was placed on

the psychological skills of candidates to select individuals with the appropriate attitude for the post. In this approach, those with exceptional intellects who cannot perform assigned tasks would be chosen. The provision of in-house training facilities was made for creating course materials on IT and electronic platforms to improve skills.

A system that is effective for talent management and succession planning requires a performance management procedure that is both fair and objective. Bhatt (2013) recognized an insufficient research base for developments in human resource management strategies and practices; consequently, recruiting, retention, and pay strategies implemented by Indian banks require special consideration. AL-Zahrani et al. (2014) found a significant association between financial success and efficient human resource procedures in Saudi banks. They found a correlation between the economic success of banks and human resource strategies such as workforce planning, job description, compensation system, and performance review.

Muhammad et al., (2015) examined bank performance in Bangladesh using data envelopment analysis in the context of human resource practices as a quality component. The study's findings revealed an acceptable level of performance of local banks with improved HR practices because of increased modernization and competition among banks. Kujur et al. (2016) identified 49 innovative human resource techniques banks use in the public and commercial sectors. According to the findings, banks would gain a competitive edge worldwide if they adopted new and innovative HR practices. Innovative practices such as the availability of bank communities on social media, result-oriented recruitment and selection, continuous training need assessment, career development practices, team building and handling grievance procedures necessitate moving in the dynamic business environment.

2.9 HR analytics application in banking

The financial services sector globally experiences diverse disruptors, from the regulatory landscape to the rise of digitization. The capital and inputs required for the banking sector are related to 'information and knowledge.' The fields of 'information' and "knowledge" are highly dynamic. The paradigm changes in the industry have far-reaching consequences.

With the rapidly evolving regulation and compliance requirements in the financial and banking sector, a transformational approach must be addressed to boost growth. The financial industry is viewed as more conventional and less receptive to adopting new "cutting-edge" technology, which creates difficulty for HR teams to recruit top performers who want flexible work schedules and technologically advanced workplaces in the modern corporate climate. Human resource leaders working with financial services are considered faster at adopting data and analytics than other job roles. Chief executives of the financial sector acknowledge that technology has the potential to improve transparency and connectivity. The industry is reviewing its people strategies to meet the changing skills requirements.

Studies highlighting the need and application of analytics in banking are discussed in this section:

Devlin (1997) emphasized the importance of reputation, image, and excellent service when establishing a competitive edge in the banking industry. Likewise, Chen (1999) stressed the importance of human factors in competitive bank strategies. The banking industry had to confront new challenges in the twenty-first century. Modern business models must consider digitalization, new regulations, and changing customer expectations. The human factor is essential to achieving a competitive edge in virtual reality. As a result, collaboration between HR and Finance is on the rise in the financial services industry, with a majority of eighty (80) % of organizations working together to make data-driven recommendations and plan for the future.

Husselid and Becker (2005) stated in their study that technology opportunities allow for faster development in several business areas due to the data-driven organizational decision-making processes. Hassan et al. (2006) evaluated employee views of human resource development techniques in employee development and quality focus in firms. The study involved the collection of data from 229 employees of eight companies. Results showed a wide range of HR practices used by organizations. The combined effect of the HR performance index and employee turnover and productivity significantly predicted firm performance. In their 2008 study, Mellacheruvu and Krishnamacharyulu cited insufficient recruiting in public sector banks and a lack of personnel to suit the needs of banks. These financial institutions failed to give training. The bank's appraisal system was in fashion and required to be reformatted to make it more objective and linkable to its objectives. The rigidity of

the rewards and promotions system was not correlated with performance, and banks provided less compensation to employees than other organizations, which caused problems in retention and succession planning at the banks.

Jon Ingham (2011), the purpose of the study was to facilitate the role of analytics in people management and business to enable strategic decision-making. The methodology adopted was analyzing two companies' case studies to establish the link between strategy and analytics. The results concluded that companies require a human capital scorecard that links human resource activities and output. The broad adoption of enterprise resource planning and human resource information systems, according to Gardner et al. (2011), has made data on operations, performance, and staff more accessible and standardized. Using software and technology, HR and business leaders analyze data to identify connections between talent management and employee productivity—industry dynamics, talent scarcity, growth rates, and corporate culture influence the banking industry. Banerjee et al., (2013) found that the BFSI, Telecom Services, ITES, FMCG, and Retail industries account for a sizable portion of analytics use. Business analytics encompasses the past, the present, and the future to provide more knowledge, superior information, and concrete insights. Analytics gains value as it transitions from descriptive to prescriptive applications. Companies can discover labour trends and develop a cost or revenue model with the help of new HR analytics apps. Prosvirkina (2013) evaluated banks' HR effectiveness and organizational performance and discovered that multinational banks use HR technology more than domestic banks. The advancement of HR technology has a favorable effect on an organization. Gupta et al., (2016) examined the landscape of human resource analytics and identified factors that influence the acceptance of analytics among human resource professionals. It has been determined that analytical skills are the most critical factor, although the organizational scale is a significant factor. Meles et al., (2016) discovered that human capital impacts bank profitability more than other intellectual capital components (structural and physical). Higher levels of human capital productivity are associated with enhanced bank performance. Banks must be able to evaluate human resources using cutting-edge technologies. They must diversify away from interest-generating assets (loans) and towards non-interest-generating enterprises (Bermpei 2018, Ahamed 2017). HR Analytics significantly impacts the bank's data consolidation, performance management, and compensation

management, according to Ignacio et al. (2017). In addition to HR Analytics, the organization's relationships and culture are essential for resolving human resource-related challenges. The digital society, which embraces online banking and cashless transactions, places a premium on real-time experiences and utility (Mbama & Ezepeue, 2018). Ali Q et al. (2020) found that extensive data analytics influence banks' financial and sustainability performance. Bank organizations must commit to the necessary data monitoring to accomplish operational efficiency and sustainability objectives. The digital revolution altered client expectations. It has produced a new type of customer that is connected, app-native, and conscious of the opportunities and potential of technology. The banking industry's digital transformation involves alternate customer-facing channels like Internet branches, chatbots, and robotics. The components built applications to enable banks to communicate with consumers on different platforms. Historically, modern technologies have automated manual jobs (Kaur et al., 2020). The fourth industrial revolution increased the pressure on banks to retain and establish customer ties. The core goals of Banking 4.0 align with the technology of Industry 4.0 for digitizing assets, establishing a virtual identity, offering clients special offers, and personalization Mehdiabadi et al., (2020). The 2020 research from KPMG highlighted user-friendly and intuitive interfaces, cyber security, and personal client financial management. Implementing new technology necessitates a competent staff able to meet the requirements. The immediate effects of EU rules were increased capital requirements and recent posts in compliance, data security, and IT departments.

Adesina (2021) investigated the effect of intellectual capital (and its components) on banks' cost, allocative, and technical efficiency and discovered that human capital was positively correlated with all efficiency indices. Fintech titans, startups, and IT titans are innovating and experimenting with new goods and distribution channels that change the ordinary function of banking. The COVID-19 financial crisis has driven innovation and digitalization in the banking sector (Demirguc Kunt et al., 2021). Banks must be able to produce new skills and employment in order to survive. Banks must be flexible and open to exploring innovative solutions to flourish in an uncertain environment. Lailatullailia et al., (2021). Arora et al. (2022) examined the factors influencing an individual's decision to adopt human resources (HR) analytics. The study outcomes identified performance expectations, hedonic incentives, and data

availability contributing to adopting HR Analytics. After studying papers about the use of analytics in banking, it has been determined that HR Analytics can revolutionize the HRM function for improved decision-making and the creation of effective HRM interventions.

2.10 Role of HR analytics in decision making

Decision-making is the core of managerial planning. However, management often makes decisions based on vague, incomplete, and uncertain information from the past. The organizational decision-making process constitutes subjectivity and lack of evidence, generating the need for further research in data-driven decision-making. Business organizations are focused on practices based on facts and evidence, helping managers to facilitate better decisions with available data to frame strategies. Predictions based on results are gaining recognition for human resource decision-making in organizations.

Analytics is the logical method that provides an evidence-based approach to decision-making. With the help of analytics, HR professionals get the validity of their outcomes and provide the right direction for the profitability of the organizations based on results.

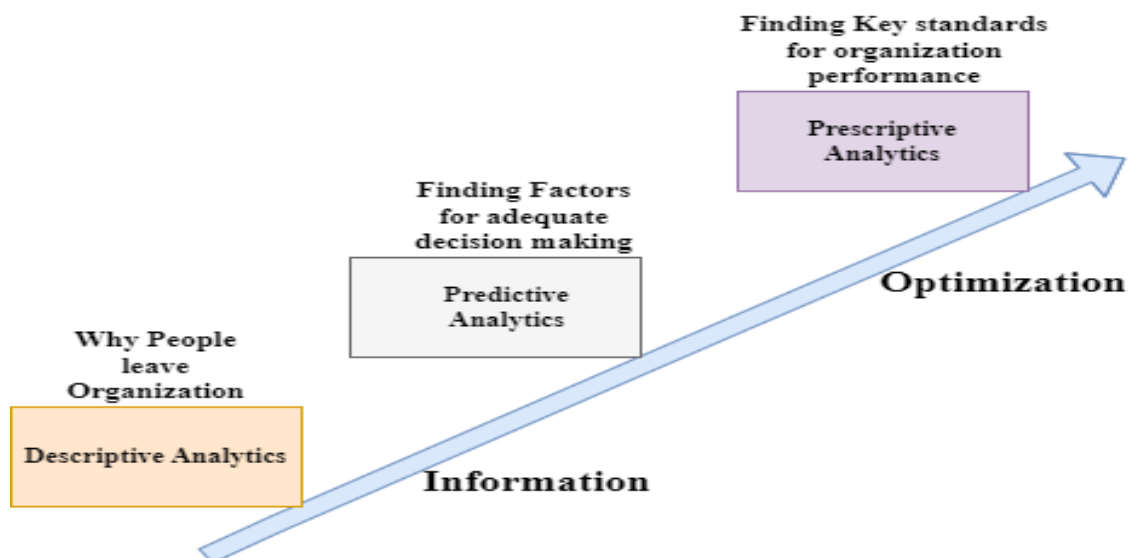


Figure 2.3: Types of Analytics

Studies highlighting the role of HR analytics in decision-making are discussed in this section:

According to Bellman and Zadeh (1970), a most practical decision-making scenario occurs where potential actions' goals, restrictions, and consequences are unknown. Human capital analytics allows for the early identification of insights (Wally, S. and R.J. Baum 1994). The importance of data mining in Human Resource Management Systems (HRMS) to a company's competitive position and organizational decision-making was underlined by Ranjan J. et al. (2008). The study found that data mining promotes performance and improves decision-making quality.

HR analytics serves as a tool for firms to uncover the intended outcomes. Analytics is essential for businesses to investigate the relationship between performance, outcomes, and profits, which directs the organization toward its objective. Human capital analytics provides a methodical method for analyzing the probable future performance of employee stocks.

It is utilized for predictive management. To increase one's capacity to employ business analytics, decision-makers must update their abilities (such as mathematics, statistics, econometrics, and IT). In his study, Jon Ingham (2011) addressed using analytics in people management and business to aid strategic decision-making. A case study technique involving two organizations established a link between strategy and analytics. According to the results, firms need a human capital scorecard to link human resource activities and output. According to Kapoor and Sherif (2012), HR analytics collects and maintains data for predicting trends in the supply and demand of employees in various industries and occupations to aid global organizations in making decisions regarding optimal talent acquisition, development, and retention human resources. Cao et al. (2015) developed a study model linking business analytics to DME within companies. According to the study's primary findings, business analytics increased information processing capability by facilitating a data-driven environment, positively impacting DME. The study contributed to the manager's knowledge by demonstrating how business analytics can improve DME.

In their study, Wei and Varshney (2015) described Optigrow as an extensive data method that enables IBM to transform by transferring skilled employees from lagging sectors to expanding ones. According to Angrave (2016), HR analytics facilitates the discovery of performance enhancement factors and quantifies the return on

investment. The technique for applying analytics began with the formulation of questions, the specification of a logical research design, the meaningful organization of data, and the use of proper statistical modelling. Mishra et al. (2016) presented a framework for making HR-related choices, incorporating data mining and predictive analytics. The suggested architecture relies on data warehousing and mining and, if wholly implemented, improves the decision-making power of human resources. In addition, a statistical algorithm was devised to prioritize transferring internal applicants to employment in growing areas. This type of data-enabled internal transfer can provide enterprises with substantial financial benefits.

HR analytics helps human resource professionals make rational decisions by enhancing the strategic impact of human resources on corporate success (Singh, 2016). HR Analytics allows businesses to collect and analyze high-quality data to determine the ROI of HR investments and make human resource-related choices based on solid evidence. Reddy et al., (2017). Human resource data enhances decision-making by giving HR professionals and line managers' workforce support information (Houghton & Green, 2018). Furthermore, human resource analytics utilized data to enable evidence-based decisions that increase value and promote sustainability.

In their research, Opatha (2020) discovered that HR analytics provides a data-driven framework by aligning software and statistical models, which delivers fresh insights for wiser decision-making and enables managers to optimize their investments in human resource management.

In their study, McCartney et al. (2022) developed a chain model that offers access to HR technology and enables the implementation of HR analytics, enhancing organizational performance.

2.11 Research gaps

Reviewing previous scholarly works had increased information and aided in achieving the objectives of the present study. Analytics had been a game-changer for firms' human resource departments. (Sheng et al., 2017; Shang et al., 2019; Grover et al., 2020) Human resource analytics enabled an organization to make data-driven, objective employment decisions.

Due to its significant impact on operational and strategic decision-making, businesses were spending more on analytics. (Momin, 2014; Patre 2016; Marler and Boudreau, 2017; Sharma and Sharma, 2017) Human resource analytics catalyzed for businesses to attain their intended performance outcomes. As a result, HR professionals placed a greater emphasis on predictive outcomes for decision-making.

Evidence-based management techniques were increasingly based on scientific conclusions through processed data and objective organizational facts. Due to the increased awareness of such methods, analytics emerged from market requirements and became a crucial instrument for corporate requirements. Human resource directors were transitioning from making reactive decisions based on historical reports and dashboards to correlating human resource data with business data to anticipate future results, as discovered by the study. As per Cornell University's 2010 study titled "State of HR Analytics" showed that the primary application of human resource analytics lay in forecasting the future.

Organizations required a technological application; that transformed data and information into intelligence for business decision-making which would positively impact organization development. There is a need for decision-making to be supported by scientific evidence for more effectiveness and efficiency (Baker, 2002). Analytics had caused more managerial hurdles than technology in terms of impeding the widespread adoption of human resource analytics due to a lack of awareness regarding the application of analytics in enhancing decision-making. (Rasmussen and Ulrich, 2015) Limited scientific information was available to guide decision-making regarding adopting human resources analytics. Predictions of relationships based on theory were inadequate.

The availability of organizational and predictive modelling-based studies was essential. Few studies had found a correlation between human resource analytics and beneficial organizational outcomes. Human resources analytics research was dominated by qualitative case studies, which paved the path for developing management frameworks. Qualitative investigations revealed the absence of a systematic approach to human resource management in the service sector. Human resource analytics was not extensively implemented, mostly due to a lack of human

resource experts with analytical skills. As a result, analyses and resulting reports were vital and could incorporate obsolete descriptive metrics based on efficiency.

The research (Tahir et al., 2010; Abbas et al., 2019) demonstrated that private bank managers use a variety of human resources (HR) tactics to boost employee productivity. Bhatt (2013) noted that it is necessary to identify effective and inefficient techniques employed by Indian banks to attract, retain, and motivate human resources. In their study, Kujur, T et al. (2016) discovered that innovative HR strategies help banks remain competitive in the global marketplace. For decision-makers to implement HR Analytics, however, a more targeted and systematic research strategy is required. Marler H. J et al (2017).

Due to the discrepancy between analytics and data, it is necessary to research the influence of HR Analytics on organizational performance and the evolution of HR policies. Lochab et al. (2018). The key motivating problem to be addressed was contribution of human resource analytics to effective banking industry decision-making. Human resource functions must concentrate on attracting, maintaining, and motivating human resources (Deolalkar, 2010) as the quality of human resources correlates with a bank's capacity to deliver client value (Kamesam, 2004; Leeladhar, 2005). An analytical approach to human resource investments could aid firms in determining what recruitment, training and development, performance management, and retention initiatives would yield the highest returns. Using human resource analytics, administrators and practitioners could plan investments based on attainable and successful initiatives. In order to solve various business problems, complex data analysis was a value driver in human resource management (HRM).

HR analytics provided a perspective for effectively managing human resources to achieve organizational objectives efficiently and rapidly. According to studies, the essential function of human capital analytics was to generate predictive business indicators for business leaders' strategic planning and decision-making. The findings had prompted the human resource department to develop a skill analytics tool to identify enterprises' human resource difficulties. In their research, Zulfqar and Kabir Bowra (2011) identified a positive association between HR practices and employee performance. Therefore, bank organizations must recognize that HR strategies impact employee performance, impacting the private or public bank's overall performance.

Banks must commit to effective data monitoring for operational efficiency and sustainability objectives.

According to Opatha, HR analytics provided a data-driven framework with software and statistical models for improved decision-making, enabling managers to optimize investments in human resource management (2020). This study would attempt to fill a few holes in the existing literature. HR analytics enhanced management and improved evidence-based organizational decision-making if advantages are adequately weighed and contextualized. The research foundation supporting big data and HR analytics was deemed insufficient (Rasmussen & Ulrich, 2015). Most HR analytics studies focused on normative concerns instead of answering analytical questions, in what situations and with precise results (Angrave et al., 2016). Due to the need for all team members to possess analytical and business intelligence (BI) skills for faster solution and product delivery, interdisciplinary research is gaining popularity. There was a large gap between the current competency of qualified employees and the level the banking industry needs. The deficiencies in the financial sector were related to conceptual thinking, analytic abilities, and information searching. HR analytics research lagged in promoting vision and leadership within firms. According to Hüllmann and Janna Mattern (2020), HR analytics requires a solid theoretical foundation. The operationalization and measurement of the notion require much discussion.

2.12 Conclusion

Ulrich (2010) discovered in their study that HR executives avoid quantitative aspects of the business, which is no longer possible given that the role is now data-driven. Johnson et al. (2012) argued that HR professionals' commitment to time, talent, and resources would effectively develop HRIS knowledge. Angrave et al. (2016) emphasized that academics play a significant role in expanding organizations-beneficial HR analytics knowledge, including the practical application of the appropriate tools and methodology to analyze massive datasets.

Mohammed's (2019) review of the literature on predictive behavior revealed that data analytics could aid in the identification of particular factors that can facilitate both human resource management (HRM) and human resource development (HRD) inside an organization. Predictive modelling assured that raw data could be utilized to

generate meaningful conclusions and insights for the growth of a business. Predictive model diagnosis case studies were required to evaluate the relevance and viability of the models generated for specific industry sectors. According to Van Kempen et al. (2019), academics could examine ways to incorporate analytic decision-making while minimizing damage to morale and organizational commitment in light of firms' growing dependence on people analytics and the resultant relevance of perceived fairness. According to McCartney, the existing literature on people analytics is inadequate (2022). The report examined the current status of people analytics and identified the resulting disputes and challenges. The review highlighted and assessed inconsistencies between the concept and definition of people analytics, as well as ownership, ethical, and privacy concerns regarding the use of people analytics, the lack of evidence demonstrating the impact of people analytics, and the readiness to perform people analytics. In their study, Gohain (2021) found that HR investigation is widely employed in Western IT businesses; it is gaining popularity in the Indian IT market, although it has severe limitations.

Chapter-3

Research Methodology

This chapter describes the research design, methods, sampling technique, study population, sample size, preparation of research instrument, data collection procedure and statistical tools employed for data analysis. Human Resource Analytics is the independent variable, whereas Human Resource Decisions is the dependent variable. The independent and dependent variables will be analyzed further in the research design.

3.1 Research Questions:

RQ1: What are the factors influencing the need for Human Resource Analytics?

RQ2: What is Human Resource Analytics used for?

RQ3: How does Human Resource Analytics affect human resource functions?

3.2 Research Objectives of the Study

The study examines the factors determining the need for human resource analytics, the role of human resource analytics on decision-making, and the effect of different types of analytics.

The study draws the following objectives explicitly:

- To examine the factors bringing out the need for HR analytics in select banks
- To study the role of HR analytics on decision-making in HR functions
- To measure the effect of various types of analytics on identified HR functions.

3.3 Research Hypotheses

The hypothesis is a predictive statement that elucidates the association between the independent variable (IV) and the dependent variable (DV). For present study, different hypotheses have been formulated based on the proposed research model. The framed hypothesis is discussed as follow.

3.3.1 Research Hypotheses 1

Role of HR Analytics in decision making in HR functions

Several studies identified the role of HR analytics on decision-making in HR functions. It is essential to examine the historical data, cause-effect analysis of past decisions and 'what if' scenarios for effective implementation of HR analytics. Analytics in HR practices and processes use analytic capabilities to make decisions (Lawler et al., 2004). HR analytics involves the application of descriptive, visual and statistical analyses related to HR processes to establish business impact and leads data-driven decision-making (Bassi, 2011; Rasmussen & Ulrich, 2015; Marler et al., 2017). HR analytics enables evidence-based decision-making with actionable insights (Jain et al., 2017). HR Analytics aids HR managers in making decisions backed by data-based evidence. HR managers utilize HR predictive analytics to predict human behavior and optimize performances for a better return on investment in organizations through decision-making based on predictive analysis tools (Mohammed, 2019).

Hypotheses have been framed as mentioned below:

H1: Higher the intensity of using descriptive analytics in a bank, the greater the effectiveness of decision-making in HR functions

H2: Higher the intensity of using prescriptive analytics in a bank, the greater the effectiveness of decision-making in HR functions.

H3: Higher the intensity of using predictive analytics in a bank, the greater the effectiveness of decision-making in HR functions.

3.3.2 Research Hypotheses 2

Effect of various types of analytics on identified HR functions

Sharma et al., 2017 found in their research application of HR analytics is negatively related to subjectivity bias in performance management function. The application of analytics tools enables high return on investment for recruitment (Ben-Gal 2019). Predictive HR analytics has a positive relationship and significantly enhances the outcome of recruitment, performance management, training and development and retention of employees (Srividya et al., 2021).

3.3.2.1 To measure the effect of various types of HR analytics on recruitments in banks

H4: Higher the use of descriptive analytics; more-updated is the recruitment database in select banks

H5: Higher the use of descriptive analytics; easier is the recruitment in select banks

H6: Higher the use of descriptive analytics; greater is the quality of recruitment in select banks

H7: Higher the use of prescriptive analytics; more-updated is the recruitment database in select banks

H8: Higher the use of prescriptive analytics; easier is the recruitment in select banks

H9: Higher the use of prescriptive analytics; greater is the quality of recruitment in select banks

H10: Higher the use of predictive analytics; more-updated is the recruitment database in select banks

H11: Higher the use of predictive analytics; easier is the recruitment in select banks

H12: Higher the use of predictive analytics; greater is the quality of recruitment in select banks

3.3.2.2 To measure the effect of various types of HR analytics on training and development in banks

H13: Higher the use of descriptive analytics; greater is the use of post training analytics in select banks

H14: Higher the use of descriptive analytics; greater is the use of financial analytics of training in select banks

H15: Higher the use of descriptive analytics; greater is the use of training for skill-gap in select banks

H16: Higher the use of prescriptive analytics; greater is the use of post training analytics in select banks

H17: Higher the use of prescriptive analytics; greater is the use of financial analytics of training in select banks

H18: Higher the use of prescriptive analytics; greater is the use of training for skill-gap in select banks

H19: Higher the use of predictive analytics; greater is the use of post training analytics in select banks

H20: Higher the use of predictive analytics; greater is the use of financial analytics of training in select banks

H21: Higher the use of predictive analytics; greater is the use of training for skill-gap in select banks

3.3.2.3 To measure the effect of various types of HR analytics on performance management in banks

H22: Higher the use of descriptive analytics; greater is the use of skill competency analytics in select banks.

H23: Higher the use of descriptive analytics; greater is the use of promotion competency analytics in select banks

H24: Higher the use of descriptive analytics; greater is the use of satisfaction and productivity analytics in select banks

H25: Higher the use of prescriptive analytics; greater is the use of skill competency analytics in select banks

H26: Higher the use of prescriptive analytics; greater is the use of promotion competency analytics in select banks

H27: Higher the use of prescriptive analytics; greater is the use of satisfaction and productivity analytics in select banks

H28: Higher the use of predictive analytics; greater is the use of skill competency analytics in select banks

H29: Higher the use of predictive analytics; greater is the use of promotion competency analytics in select banks

H30: Higher the use of predictive analytics; greater is the use of satisfaction and productivity analytics in select banks

3.3.2.4 To measure the effect of various types of HR analytics on retention in banks

H31: Higher the use of descriptive analytics; greater is the use of retirement analytics in select banks

H32: Higher the use of descriptive analytics; greater is the use of service analytics in select banks

H33: Higher the use of descriptive analytics; greater is the use of comparative turnover analytics in select banks

H34: Higher the use of prescriptive analytics; greater is the use of retirement analytics in select banks

H35: Higher the use of prescriptive analytics; greater is the use of service analytics in select banks

H36: Higher the use of prescriptive analytics; greater is the use of comparative turnover analytics in select banks

H37: Higher the use of predictive analytics; greater is the use of retirement analytics in select banks

H38: Higher the use of predictive analytics; greater is the use of service analytics in select banks

H39: Higher the use of predictive analytics; greater is the use of comparative turnover analytics in select banks.

3.4 Research Model

The Research Model of the present study is given in figure 3.1 where descriptive research is conducted ending with data analysis of the collected data.

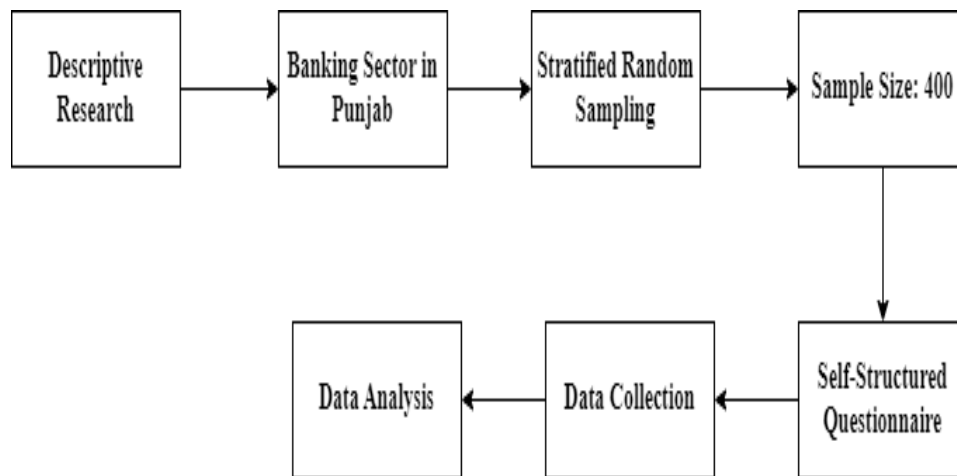


Figure 3.1: HR Analytics and HR Decisions

3.5 Research Design

The present study is quantitative. The purpose of this research is descriptive to comprehend HR analytics requirements and the role of human resource decision-making in a banking organization. The research involves correlation and causal investigation. The study is a field study conducted under actual conditions. The respondents in the current study were managerial-level employees from select banking organizations in Punjab who knew the factors that drive the need for human resource analytics, the role of human resource analytics in decision-making, and the impact on specific human resource functions. Senior and Human Resource Managers working in Punjab's banking sector provided the information.

3.6 Target Population of Study

The target population for this study includes the banking sector of Punjab. The scheduled, non-scheduled, and development banks make up the bulk of banking industry. Scheduled banks comprise public, private, foreign and regional rural sectors.

The study identified public and private banks basis on their consistently high performance from (2014 to 2019) in terms of net profits and total assets. The study population includes HR Managers and Senior Managers working in the banks.

3.7 Method of Sampling

The sample frame was created using the most recent lists and directories from the Indian Bank's Association and the Reserve Bank of India (<https://rbi.org.in/scripts/banklinks.aspx> and <https://www.iba.org.in/depart-res-stcs/key-bus-stcs.html>). These directories comprised information regarding the number of branches, number of employees, profit per employee, year of establishment, net profit and total assets.

As a sampling technique, random sampling has been utilized. Additionally, stratified random sampling was used to determine the sample. Using Scheduled Commercial Banks Classification, this study classifies the banking sector in Punjab into two basic categories. The classes include i) Banks in the public sector (ii) Banks in the private sector. Two types of banks are viewed as population strata, each comprising enterprises with similar characteristics. The analytical units for this study are bank branches. Each bank had at least two respondents; one was the human resources manager and the other was a senior manager experience in human resources. The respondent's job title, position, and duties within the company were evaluated before responses were recorded.

Table 3.1: List of identified Public and Private Sector Banks for study

Types of Banks	Bank Name	Establishment	Head Quarter	Total Branches in Punjab
Public Banks	Bank of Baroda	1908	Vadodara, Gujarat	89
	Bank of India	1906	Mumbai, Maharashtra	105
	Canara Bank	1906	Bengaluru, Karnataka	106
	Punjab National Bank	1894	New Delhi, Delhi	195
	State Bank of India	1955	Mumbai, Maharashtra	547
Private	Axis Bank	1993	Mumbai,	310

Banks			Maharashtra	
	HDFC Bank	1994	Mumbai, Maharashtra	441
	ICICI Bank	1994	Mumbai, Maharashtra	185
	Kotak Mahindra Bank	2003	Mumbai, Maharashtra	100
	YES Bank	2004	Mumbai, Maharashtra	197

Table 3.2: Scale levels in Public and Private Banks

Types of Banks	Grade	Designation
Public Sector Banks	Scale 0	Clerks
	Scale 1	Officer/Assistant Manager
	Scale II	Manager
	Scale III	Senior Manager
	Scale IV	Chief Manager
	Scale V	Assistant General Manager
	Scale VI	Deputy General Manager
	Scale VII	General Manager
Private Sector Banks	Scale VIII	Chief General Manager
	E1	Assistant Manager
	E2	Deputy Manager
	E3	Manager
	E4	Senior Manager
	D1	AVP
	D2	DVP

Total number of Branches of all the ten banks in Punjab region is 2,275.

The sampling frame for the survey is selected from Public and Private Banks in Punjab and constructed based on the large availability of banking branches. For this study, the sampling unit was Senior Branch and HR Managers who are the

practitioners of HR policies in a total of 22 districts of Punjab for banks using HR Analytics for HR Decisions.

Table 3.3: Estimated Number of Public and Private Banks in Punjab

Type of Bank	Bank	Branches in Malwa	Branches in Majha	Branches in Doaba	Proportionate Branches Selected
Private Sector Banks	Axis Bank	171 (14)	76 (6)	63 (5)	25
	HDFC Bank	232 (19)	94 (7)	115 (9)	35
	ICICI Bank	121 (9)	32 (3)	32 (3)	15
	Kotak Mahindra Bank	60 (5)	10 (1)	30 (2)	8
	YES Bank	50 (4)	40 (3)	107 (9)	16
Public Sector Banks	State Bank of India	350 (34)	94 (9)	103 (9)	52
	Bank of Baroda	53 (5)	14 (1)	22 (2)	8
	Bank of India	53 (5)	23 (3)	29 (3)	11
	Canara Bank	57 (5)	19 (2)	30 (3)	10
	Punjab National Bank	55 (5)	59 (6)	81 (5)	16
	Total				

3.8 Sample Size

The proportionate sampling was done in Table 3.3 after the estimated 2,275 bank branches in the Punjab region. An estimate of the number of bank branches in each of Punjab's three regions was provided after selecting carefully selected banks. The fourth column proportion is calculated by dividing the total number of units in each area by the total number of bank branches in Punjab, then multiplying the results by 100. Each bank branch submitted at least two responses. In the end, 473 responses had been submitted. Four hundred individuals were chosen as samples for current inquiry.

3.9 Designing of Research Instrument

The research instrument was based on the design of proposed research model of this study. The research instrument is formed with a combination of question statements related to the variable under investigation. The study variables include human resource analytics as the independent variable and human resource decision-making as dependent variable. Three sections make up the survey instrument. First, 14 statements were considered to analyse the current state of HR analytics. The effectiveness of human resource function statements includes the overall performance of HR department, well defined roles and responsibilities of the HR department; the HR department adding value to the business and the preferred existing working style (Barney and Wright, 1998). For human resource functions, the recruitment function consists of 14 statements, the training and development function consists of 14 statements, performance management consist of 12 statements and retention consists of 12 statements. The present study has employed a widely used seven-point Likert scale to measure the constructs of the study. The scale responses ranged from 1 (strongly disagree) to 7 (strongly agree), with a neutral point of 4 (neither agree nor disagree). The seven-point scale is considered precise to aid respondents in completing the questionnaire or survey instrument and is widely used in studies.

3.10 Structure of Research Instrument

The present study is descriptive and focuses on two variables Human Resource Analytics and Human Resource Decision Making. The purpose is to investigate the reasons driving the need for HR analytics and the impact of HR analytics on HR decision-making. In addition, the impact of various forms of analytics on certain HR operations is measured.

In the first section, statements related to the current use of HR analytics were framed. Statements asked related to the application of analytics has integrated use for HR functions, the organization's current state of HR decisions based on data analysis, access to different types of dashboards for decision making, HR policies revised and updated on the basis of data analysis, adequate use of analytics for decision making, shift to data based decisions proved effective, data analytics for monitoring key

standards of organizational health, data analytics for identification of individuals which needs attention, data analytics for identification of departments which needs attention, data analytics for determining organizational function having greatest impact on bottom line, data analytics for forecasting performance levels, data analytics for learning why people stay in organization, data analytics for learning why people leave the organization use of data analytics for adapting workforce to changes in business environment.

In the second section, statements related to effectiveness of decision making in human resource functions were asked. Questions asked related to overall HR department is performing its job the way it is expected to perform, the HR department has been able to meet expectations by executing its roles and responsibilities in a well defined manner, HR department adds value to our business activities and the HR department works in such a way that I would not like to see any change in its existing working style.

In the third section, statements related to human resource functions were asked. Questions related to awareness about the number of vacancies for recruitment, the updated database for total manpower quantity recruited, determination of internal hiring in every recruitment cycle, external hiring rate in every recruitment cycle, minimizing time to recruit in every cycle, demonstration of adherence to ethical code, higher offer acceptance rate in the recruitment cycle, reduction in the cost of recruitment, the system for speed of hiring candidates, ease of recruitment on the basis of organizational roles, the difficulty of recruitment based on administrative roles, cost for hiring the external employee, quality of recruits with performance level, tracking first-year turnover were asked for recruitment function. Questions about tracking the duration of annual training hours, expenditure per employee on training and development, initiatives for identification of priority skills gap, investment in training as a percentage of profit, investment in training as a percentage of payroll, investment in training as a percentage of revenue, percentage of employees receiving training annually, percentage of employees with competency development plans, and tracking learner's activity and value. Assessment of total promotions over total transfer in each fiscal year, competency level skill inventory for each branch, system to track satisfaction of new hires, percentage of staff working at acceptable level of performance in each branch, measurement of staff competencies to deliver business

objectives, measurement of educational level of staff at each hierarchical level, and effectiveness of performance management. Questions regarding tracking employee turnover of best performers, tracking average length of service for staff, determining average length of service by region, the average size of service by function, average years of experience for each branch, assessing reasons for employees leaving the organization, measuring annual turnover of employees in key positions, predicting involuntary staff turnover rate in the organization, and predicting voluntary staff turnover rate in the organization.

3.11 Development and Validation of Research Instrument

An extensive literature review had been done to generate items for measuring the dimensions of the constructs.

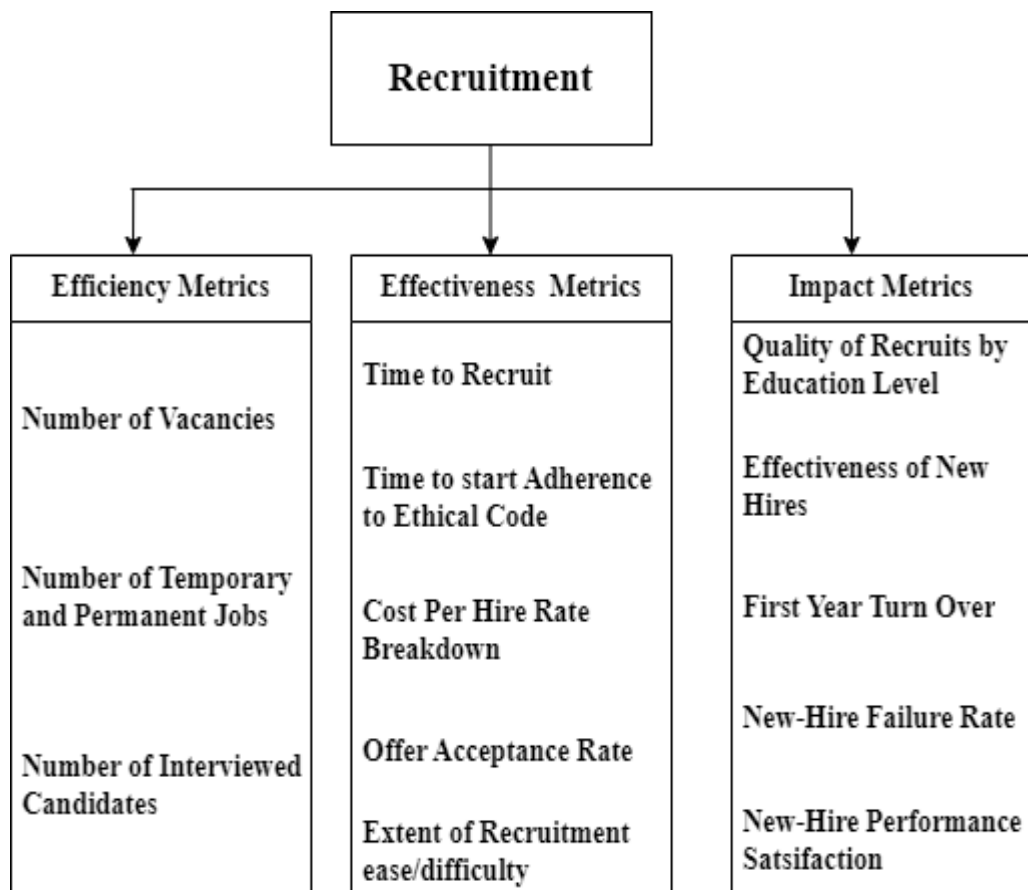


Figure 3.2: Questionnaire items of recruitment and their reference

Table 3.4: Research instrument for Recruitment

Recruitment Function	
Re_S1	This organization's HR executives are aware about number of vacancies for recruitment.
Re_S2	This organization's human resource function maintains updated database for total manpower quantity recruited.
Re_S3	This organization determines internal hiring rate in every recruitment cycle.
Re_S4	This organization determines external hiring rate in every recruitment cycle.
Re_S5	This organization minimizes time to recruit in each recruitment cycle.
Re_S6	The applicants demonstrate adherence to ethical code during interview.
Re_S7	This organization tends to maintain higher offer acceptance rate in every recruitment cycle.
Re_S8	This organization reduces cost of recruitment in every cycle.
Re_S9	There is a system of tracking speed of hiring candidates in this organization.
Re_S10	There is a system to identify ease of recruitment on basis of organizational roles (Assistant Manager, Deputy General Manager, Chief General Manager).
Re_S11	There is a system to identify difficulty of recruitment on basis of organizational roles (Assistant Manager, Deputy General Manager, Chief General Manager).
Re_S12	This organization determines cost for hiring the external employee in the company.
Re_S13	. This organization determines quality of recruits with their performance level.
Re_S14	There is a system for tracking first year turnover in this organization.

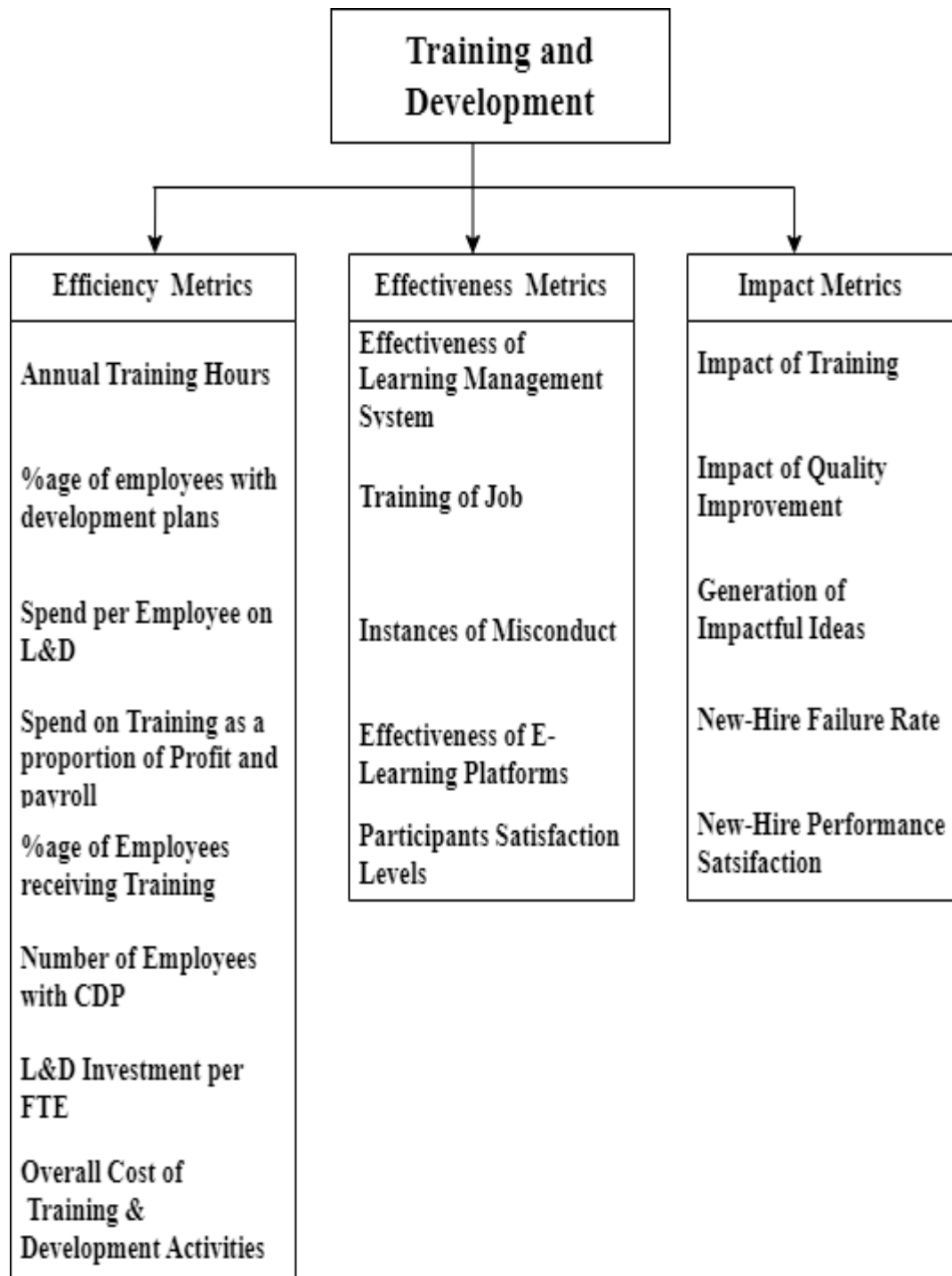


Figure 3.3: Questionnaire items of training and development with their reference

Table 3.5: Research instrument for Training and Development

Training and Development Function	
TnD_S1	There is a system to track the duration of annual training hours undergone by employee.
TnD_S2	This organization ascertains expenditure per employee on training and development.
TnD_S3	This organization adopts initiatives for identification of priority skills gap.
TnD_S4	This organization invest in training as a proportion of profit earned in a year.
TnD_S5	This organization invests in training as a proportion of payroll provided in a year
TnD_S6	This organization invests in training as a percentage of revenue in a year.
TnD_S7	This organization ascertains percentage of employees receiving training every year.
TnD_S8	This organization ascertains percentage of employees with competency development plans in a branch.
TnD_S9	A quantifiable measure to track learners' activity and value from training program is deployed by this organization
TnD_S10	This organization keeps track of instances of misconduct resulting from inadequate training
TnD_S11	This organization keeps a track of effectiveness of training programs.
TnD_S12	A system for measuring participant satisfaction levels with training activities is deployed by organization
TnD_S13	This organization determines improvement in performance post-training in each cycle.
TnD_S14	This organization determines effectiveness of quality improvement post training in each cycle.

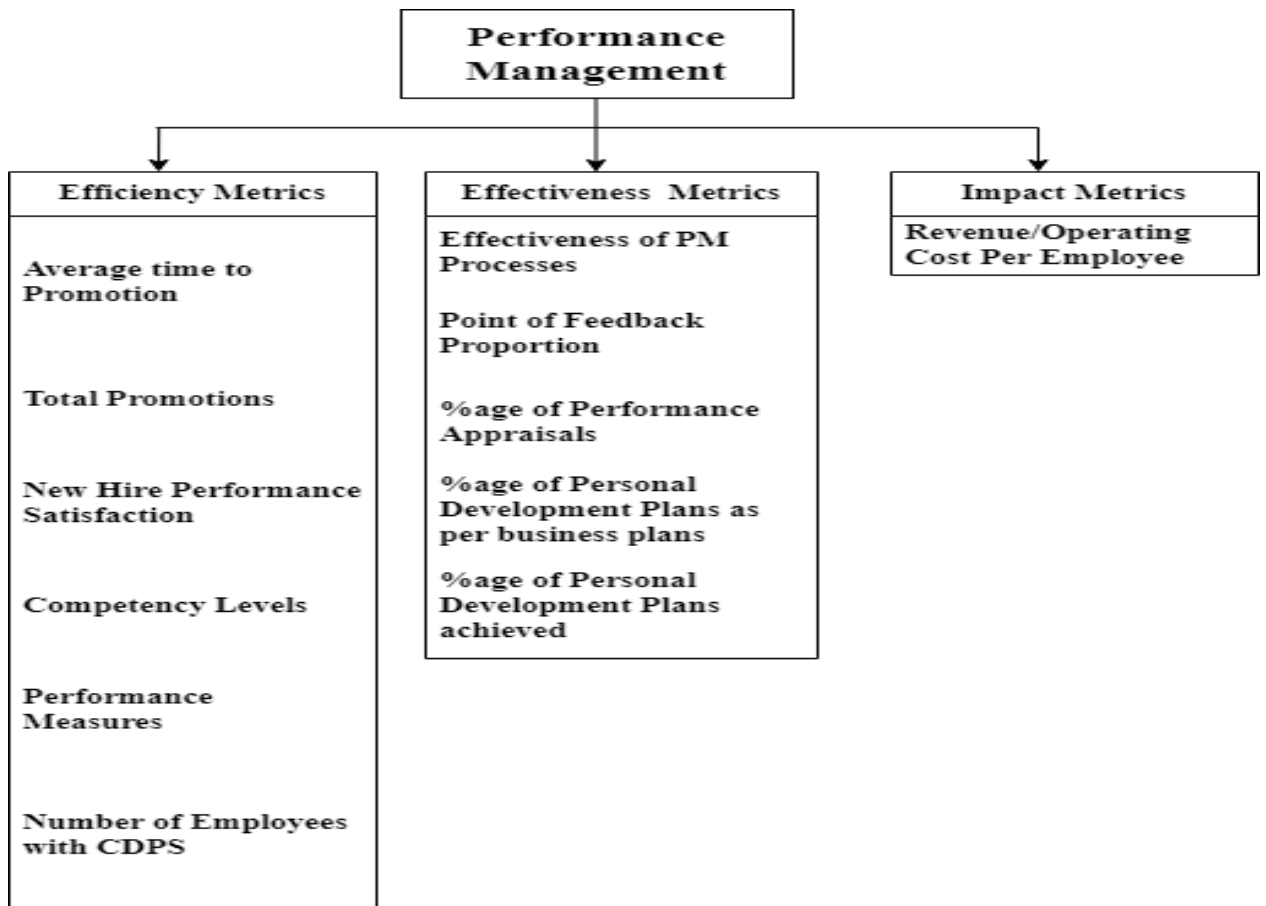


Figure 3.4: Questionnaire items of performance management with reference

Table 3.6: Research instrument for Performance Management

Performance Management Function	
PM_S1	This organization determines the average time of employees' promotion in each fiscal year
PM_S2	This organization assess total promotions over total transfer rate in each fiscal year.
PM_S3	This organization prepares competency level skill inventory for each of its branch
PM_S4	There is a system to track satisfaction of new hires in this organization.
PM_S5	This organization determines percentage of staff working at acceptable performance level in every branch
PM_S6	This organization measures staff competencies to deliver business goals in every branch
PM_S7	This organization measures educational level of its staff at each hierarchical level in branch.
PM_S8	This organization determines effectiveness of performance management processes every fiscal year
PM_S9	This organization measures extent to which performance management are aligned to business goals.
PM_S10	There is a system to measure percentage of personnel development plans complying with business plans each year.
PM_S11	There is a system to measure percentage of personnel development plans achieved by functional area every year.
PM_S12	This organization has deployed productivity measures such as revenue per employee

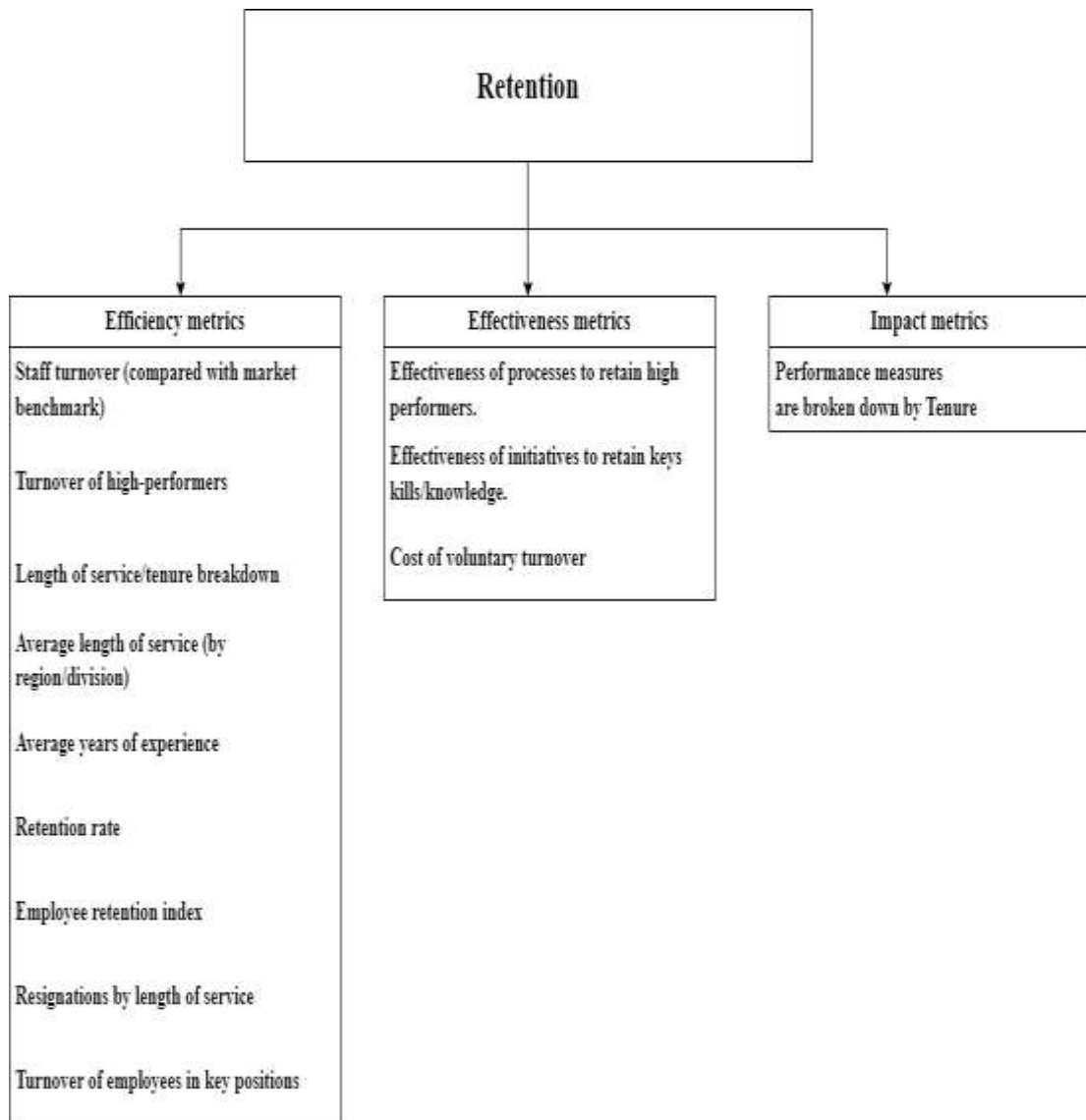


Figure 3.5: Questionnaire items of retention with reference

Table 3.7: Research instrument for Retention

Retention Function	
ER_S1	This organization determines staff turnover compared with market benchmark in every fiscal year.
ER_S2	There is a system to track employee turnover of best performers in every fiscal year.
ER_S3	This organization keeps a track of average length of service for its staff.
ER_S4	This organization determines average length of service by region.
ER_S5	This organization determines average length of service by function.
ER_S6	The average years of experience are determined for each branch in this organization.
ER_S7	There is a system to assess the reasons why employees leave the organization.
ER_S8	This organization measures the annual turnover of employees in key positions in branches
ER_S9	There is a system to predict the involuntary staff turnover rate in organization (layoffs and dismissal)
ER_S10	There is a system to predicting voluntary staff turnover rate in organization (higher studies, stay-at-home parents, relocation)
ER_S11	The average retirement rate is determined for each branch.
ER_S12	This organization determines effectiveness of process to retain high performers.

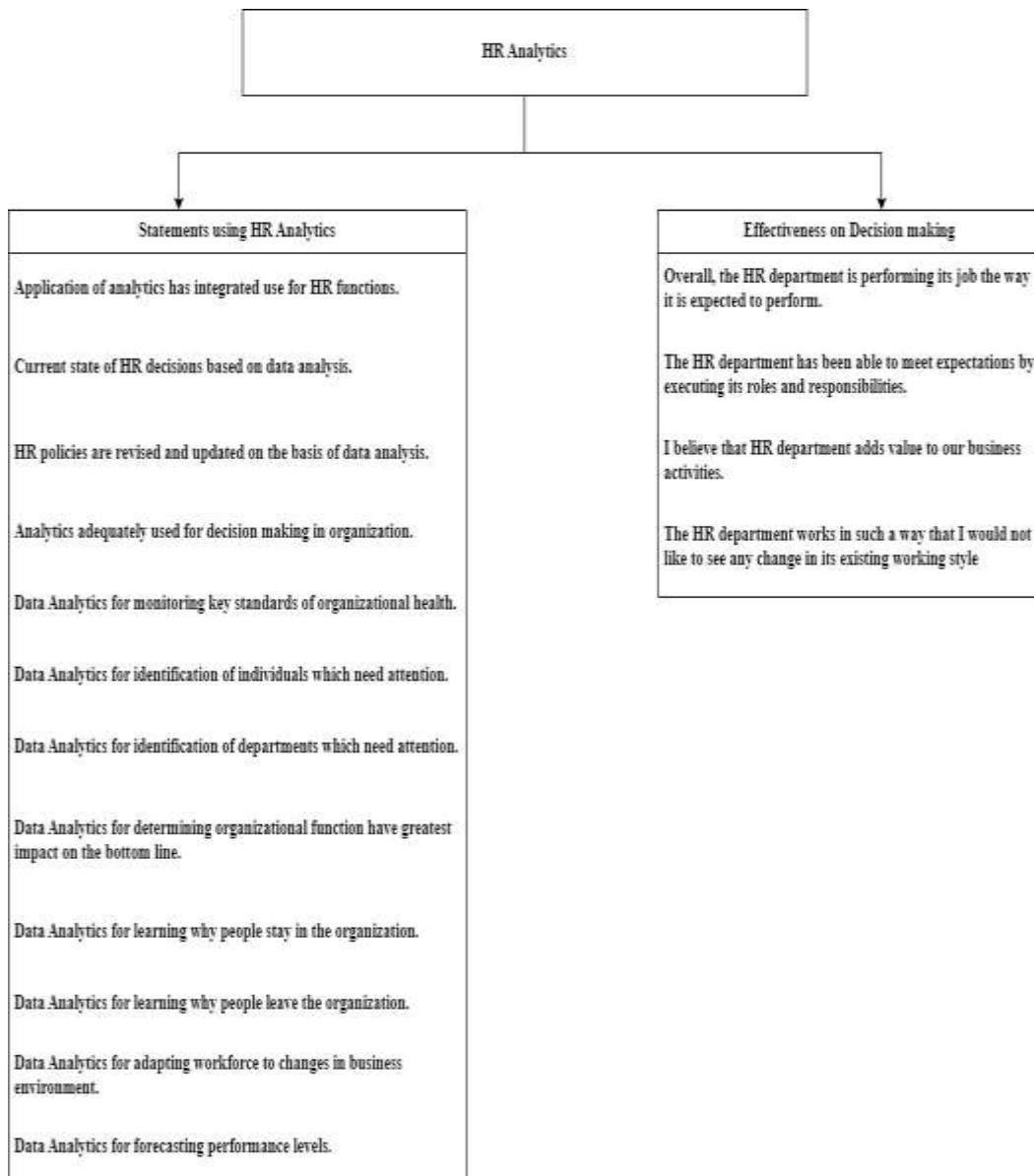


Figure 3.6: Questionnaire items of HR Analytics and HR Decision making with reference

After the dimensions of the constructs and related statements were derived from a thorough assessment of the literature, content validity was conducted. Seven academics and five industry professionals showed content validity. One item from the recruitment and two from training and development were deleted. Two items from decision-making were modified, and one was deleted.

3.12 Reliability of Instrument

Table 3.8: Reliability of research instrument

Construct	Cronbach Alpha	N of items
Recruitment	.922	14
Training and Development	.789	14
Performance Management	.811	12
Retention	.791	12
Current use of HR analytics	.868	14
Decision-making in HR functions	.809	04

The Composite Reliability (CR) for each of the five constructs is greater than the threshold value of 0.70, demonstrating the constructs' reliability (Nunnally, 1978). Table 3.8 signifies the same.

3.13 Pilot Study

Pilot testing aims to evaluate the reliability and validity of the questionnaires or survey schedule before final data collection. Before being used for the primary data collection, instruments and questionnaires must be subjected to pilot testing to discover and correct any problems (Cooper and Schindler, 2003). Fifty respondents from Public and Private sector banks with at least two years of experience in the bank participated in a pilot study. The primary objective of performing a pilot survey was to identify unsuitable measuring items, instructions, and the time required for respondents to complete the survey instrument. Based on the results of the pilot research, three statements were eliminated from the survey schedule: two from the human resource functions and one from the need of human resource section.

3.14 Primary data collection

The primary data is used extensively. The data was collected by administering questionnaires on the study's target population. Data was collected from HR and Senior Managers working in bank branches of Punjab in select Public and Private Banks. Table 3.9 signifies the types of distribution, banks and Frequency as per demographic profiles.

Table 3.9: Demographic Profile Details

Types of Distribution	Bank	Frequency	Percent
Public Banks	State Bank of India	94	23.57
	Punjab National Bank	63	15.77
	Canara Bank	19	4.78
	Bank of India	14	3.61
	Bank of Baroda	9	2.27
Private Banks	HDFC Bank	83	20.74
	Axis Bank	58	14.58
	ICICI Bank	35	8.70
	YES Bank	20	5.03
	Kotak Mahindra Bank	4	0.94
Distribution of respondents: department wise	HR	234	58.5
	Sales and Marketing	71	17.75
	Operations	43	10.75
	Accounts	52	13
Distribution of respondents: designation wise	Senior manager	165	41.25
	HR manager	148	37
	Relationship manager	38	9.5
	Branch manager	49	12.25
Distribution of respondents: qualification wise	Graduate	76	19
	Post graduate	296	74
	Above post graduate	28	7
Distribution of respondents: experience wise	0-5 years	55	13.75
	6-10 years	178	44.5
	11-15 years	92	23
	16 years and above	75	18.75
Distribution of respondents Gender wise	Male	256	64
	Female	144	36

3.15 Statistical Tool

The present study focuses on two variables viz. Human Resource Analytics and Human Resource Decisions. The data was computed in order to do the following statistical analysis:

Descriptive Analysis: This was done to obtain exploratory factor analysis for determining the underlying structure of human resource functions.

Multiple Regression determines a statistical relationship between two or more variables. This study used several independent variables of each human resource function were used to predict a single dependent variable related to decision-making.

Structural Equation Modeling: This was done to analyze structural relationships between types of analytics on identified human resource functions.

3.16 Limitations

Even though the present study was meticulously planned and implemented, it is full of few constraints for any research in any field of knowledge to do such research. Unaccounted-for external factors may have an effect on the variables under examination. The results are inconclusive. This study is a great place to start for additional analysis that could inform future empirical studies. The research is only focused to one aspect of the banking industry, and only a tiny sample from general public is used. This study's conclusions may have been affected by personal bias and possibly reluctance to give information due to the HR function being viewed as a private concern. Nevertheless, the findings are based on the integrity of information provided by respondents. Time constraints and other resource constraints prevented the selection of more participants for this study.

3.17 Summary

This section on research technique gives the framework for discovering solutions to a research problem. Five constructs were established based on a survey of the literature to achieve the goals of this study. The sampling frame for the study was Punjab. Four hundred respondents were recruited across the state. A Google form was made to capture data both during and after COVID, and personal visits were employed for follow-up. The responses that were gathered were examined using statistical

techniques such as factor analysis, multiple regression analysis, and structural equation modeling. The responses received have been examined, and the findings will be discussed in the following chapter.

Chapter-4

Result Data Analysis and Interpretation

This study aimed to find the role of human resource analytics (HRA) in the decision-making of the banking sector. The study is intended to examine how human resource analytics aids in managerial decision-making. The present chapter deals with obtained data treatment and interpretation, comprising three objectives. The first objective describes the critical variable of the study, viz. Human Resource Analytics, the second objective, shows the regression analysis between HR analytics and the effectiveness of HR functions. The third objective shows the effect of HR analytics on identified HR functions through structural equation modelling. This chapter includes data collection and audit, data coding, factors bringing out the need for HR analytics: application of Exploratory Factor Analysis (EFA), role of HR analytics on decision-making in HR functions, effect of various types of analytics on identified HR functions including recruitment, training and development, performance management and employee retention. It is evident from the objectives mentioned above that the present study requires collecting data from banks. The top five banks, one from the public and one from the private sector were chosen for the current study based on net profits made in the preceding fiscal year. On this basis, the present study has selected the following top five public and private sector banks:

Table 4.1: List of Public and Private Sector Banks

Public sector banks	Private sector banks
• State Bank of India (SBI)	• HDFC Bank
• Punjab National Bank (PNB)	• AXIS Bank
• Canara Bank	• ICICI Bank
• Bank of India (BoI)	• Yes Bank
• Bank of Baroda (BoB)	• Kotak Mahindra Bank

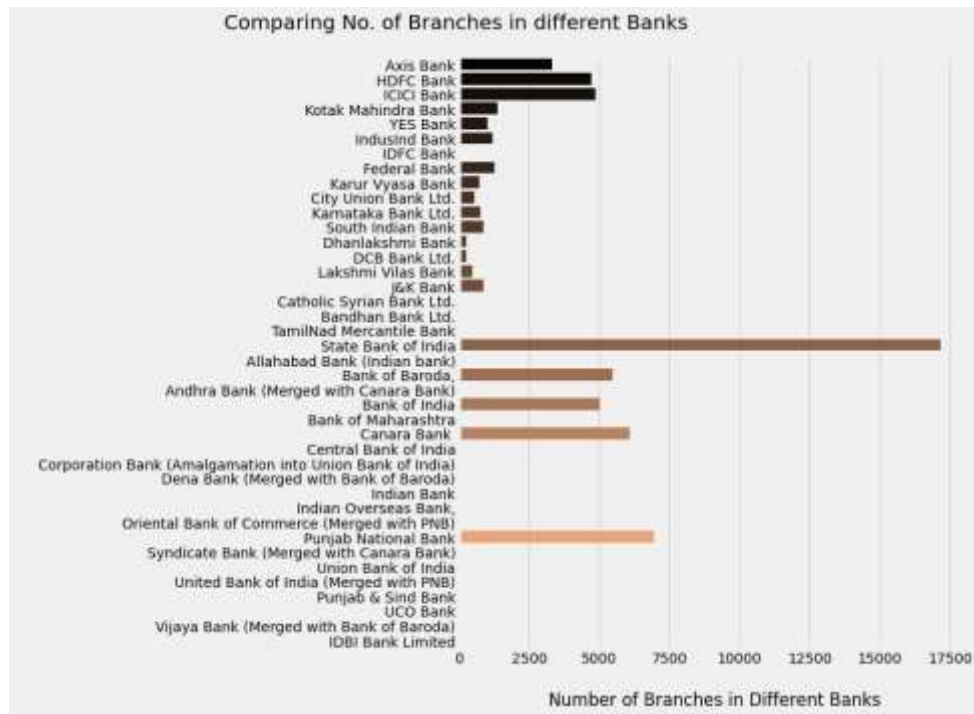


Figure 4.1: Identified Public and Private Bank Branches in Punjab

To meet the objectives, 200 respondents from public sector banks and 200 respondents from private sector banks were chosen for the study, totaling 400 respondents. Therefore, the total sample size for the study was 400, chosen from the selected bank's proportionality based on the number of bank branches present in the state. In addition, an attempt has been made to present data analysis relating to the study's objectives. Obtained data were analyzed using appropriate statistical tools such as exploratory factor analysis, structural equation modeling, multiple regression, chi-square test, percentage, frequency, etc.

4.1 Data collection and Audit

The purpose of the current study was to investigate how HR analytics affects HR functions decision-making. A self-structured questionnaire and an extensive literature review on HR Analytics and HR Decisions were used to gather the data. The questionnaire consists of 70 items: 14 statements measure the need for HR analytics, 4 statements measure perceptions of decision-making in HR functions, 14 statements measure recruitment function, 14 statements measure training and development function, 12 statements measure performance management function, and 12 statements measure retention function.

The raw data analysis must be clearly coded and accurately entered into a data file. The raw data was transferred from the survey instrument one by one to a data file in MS Excel; after examining the Excel file, this data was transferred into the SPSS file. The entered data was analyzed to detect errors made while entering this data (Cooper and Schindler, 2003). All completed instruments were checked individually at the time of data collection to ensure a minimum of missing data could be obtained. Unanswered and partially filled mechanisms were identified, and tried to get it filled accurately by the respective respondent. To ensure data cleanness, the completed data was processed through frequency distribution and missing data analysis, and no missing data has been found.

4.2 Data Coding

The demographic data of each respondent from the final database (name of bank, gender, department, designation, qualification, experience) was imported into the SPSS file. The coding template included the following sections: Current use of HR analytics (Analytics_S1 to Analytics_14); perception of decision making in HR functions (DM_S1 to DM_S4); Recruitment (Re_S1 to Re_S14); Training and Development (TnD_S1 to TnD_S14); Performance Management (PM_S1 to PM_S12) and Retention (ER_S1 to ER_S12).

4.3 Objective 1: Factors bringing out the need of HR analytics: application of Exploratory Factor Analysis (EFA)

The present study explores factors bringing out the need for HR analytics in select banks. The requirement for HR analytics in banks has been assessed using 14 statements to meet the objectives. The statements were based on integrated use of analytics application; HR decisions based on data analysis; access to dashboards for decision making; HR policies on data analysis; adequate use of analytics for decision making; effectiveness of data based decisions; data analytics for monitoring organizational health; data analysis for identification of individuals need attention; data analysis for identification of departments need attention; data analytics for determining function impacting bottom line; data analytics for forecasting performance levels; data analytics for learning why people stay in organizations; data analytics for learning why people leave organization and data analytics for adapting workforce to changes in the business environment. The questionnaire was reliable in factors bringing out the need for HR analytics, as Cronbach's alpha was .868, above

the acceptable limit of 0.60 (Hair et al., 2009). Exploratory Factor Analysis (EFA) in SPSS was applied on these statements. It is crucial to check the sufficiency of the distribution of values before doing factor analysis in order to proceed with the analysis. The same will be confirmed by looking at the Kaiser Meyer Olkin (KMO) values.

4.3.1 KMO and Bartlett's Test

First, sampling adequacy was examined using the KMO test. This test suggests that the value of KMO varies from 0 to 1; a higher value of KMO (close to 1.0) implies that applying EFA to the given data is valid. According to Costello and Osborne (2005) a KMO value statistics more than .9 is considered excellent; above .8 is considered admirable, above .7 is average; above .6 is below average, above .5 is miserable, and less than .5 is unacceptable. Second, Bartlett's Test of Sphericity was used to examine the presence of correlation among variables. This test diagnoses the relatedness of the variables considered in the study and further throws light on the detection of the factor structure. Findings of KMO and Bartlett's Test are given in the table below:

Table 4.2: “Findings of KMO and Bartlett's Test”

“Kaiser-Meyer-Olkin Measure of Sampling Adequacy”		.904
“Bartlett's Test of Sphericity”	“Approx. Chi-Square”	8935.47
	Degree of freedom	153
	“Sig. (p)”	.000
Source: Authors' Calculation		

Findings of “KMO and Bartlett's Test” (refer to table 4.7.1) highlighted that value of KMO is 0.904, which is greater than the recommended value of 0.7 (Hair *et al.* 2006). Therefore, it was concluded that the sample used in the study is adequate, which justifies the use of EFA on given data. Moreover, chi-square value for Bartlett's Test of Sphericity was found to be 8935.47 and p- value for this test was less than 0.05 (level of significance). This finding indicated the presence of significant correlation between statements relating to HR analytics. The results of both KMO and Bartlett's Test were functional in concluding that the application of EFA on given data is justified. After conducting the exploratory factor analysis, the results of exploratory factor analysis yielded three components. The results are presented in following table

4.2.1,4.2.2. Total numbers of factors obtained were three from 14 statements and named *three main variables*: descriptive, predictive, and *Prescriptive analytics*. Figure 4.2 represents a scree plot that signifies the values from largest to smallest

Table 4.2.1: Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.828	34.484	34.484	4.828	34.484	34.484	4.801	34.292	34.292
2	3.454	24.673	59.157	3.454	24.673	59.157	3.114	22.242	56.535
3	2.294	16.386	75.543	2.294	16.386	75.543	2.661	19.008	75.543
4	.758	5.412	80.954						
5	.623	4.451	85.405						
6	.503	3.595	89.000						
7	.468	3.343	92.343						
8	.375	2.675	95.018						
9	.325	2.323	97.341						
10	.158	1.131	98.472						
11	.141	1.008	99.480						
12	.041	.296	99.777						
13	.022	.160	99.937						
14	.009	.063	100.000						

Extraction Method: Principal Component Analysis.

Source: Authors' Calculation

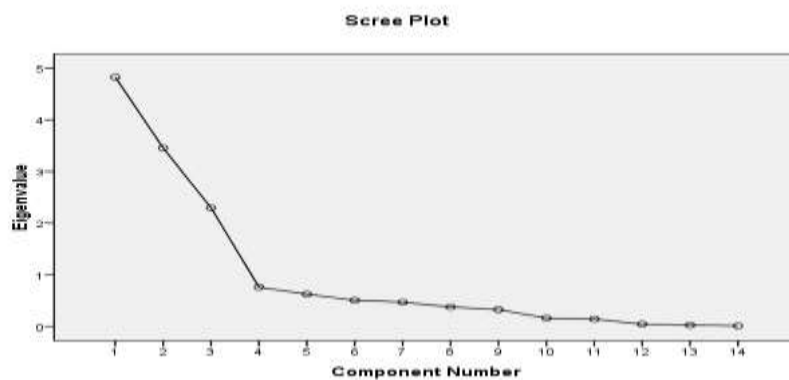


Figure 4.2 Eigen values from the largest to smallest

Table 4.2.2 Component Matrix^a

	Component		
	1	2	3
This organization's current state of HR decisions are based on data analysis	.985	.012	-.050
Bank managers' in this organization have access to different types of dashboards for decision making	.980	.006	-.066
This organization's HR policies are revised and updated on the basis of data analysis	.976	.013	-.084
This organization use Data Analytics for learning why people stay in the organization	.974	.013	-.088
This organization use Data Analytics for learning why people leave the organization	.951	.026	-.040
Analytics is adequately used for decision making in organization	.055	.740	-.384
This organization use data analytics for identification of individuals which need attention	-.046	.736	-.361
This organization use data analytics for identification of departments which need attention	-.006	.687	-.364
This organization use data analytics for determining which organizational function have greatest impact on the bottom line	-.204	.681	-.387
This organization uses data analytics for forecasting performance levels	-.144	.619	-.353
The application of analytics has integrated use across organization for HR functions	.074	.534	.691
The shift to data based decisions has proved to be effective in this organization	.080	.517	.664
This organization use data analytics for monitoring key standards of organizational health	.077	.569	.641
This organization use data analytics for adapting workforce to changes in business environment	.078	.412	.507
Extraction Method: Principal Component Analysis.			
a. 3 components extracted.			
Source: Authors' Calculation			

Table 4.2.3 Rotated Component Matrix^a

	Component	2	3
This organization's current state of HR decisions are based on data analysis	.917	-.033	.039
Bank managers in this organization have access to different types of dashboards for decision making	.879	-.029	.022
This organization's HR policies are revised and updated based on data analysis	.821	-.013	.010
This organization use Data Analytics for learning why people stay in the organization	.738	-.011	.007
This organization use Data Analytics for learning why people leave the organization	.714	-.025	.052
Analytics is adequately used for decision making in organization	.108	.873	.093
This organization use data analytics for identification of individuals which need attention	.005	.816	.103
This organization use data analytics for identification of departments which need attention	-.151	.764	.039
This organization use data analytics for determining which organizational function have greatest impact on the bottom line	.044	.748	.076
This organization uses data analytics for forecasting performance levels	-.095	.692	.037
The application of analytics has integrated use across organization for HR functions	.013	.062	.773
The shift to data-based decisions has proved to be effective in this organization	.022	.119	.749

This organization use data analytics for monitoring key standards of organizational health	.021	.062	.673
This organization use data analytics for adapting workforce to changes in business environment	.033	.060	.619
Extraction Method: Principal Component Analysis.			
Rotation Method: Varimax with Kaiser Normalization.			
a. Rotation converged in 4 iterations.			
Source: Authors' Calculation			

4.3.2 Factor 1: 'Descriptive analytics.'

Findings of Exploratory Factor Analysis (EFA) produced three factors, and the first factor was named 'descriptive analytics', which included five statements. 'Descriptive analytics' was the most significant factor in explaining variance in the data. The factor was able to explain 26.67% variance in the data. It was observed that respondents have positive perceptions of 'descriptive analytics' used in their organizations. Respondents believed that their organization has been using a wide range of historical data to draw comparisons that may be useful for making HR-related decisions in the bank. Bank managers agreed that their organization has been using data analytics to learn why people stay or leave the organization. It seems to be important from an HR point of view as descriptive analytics would help them to identify natural causes of employee attrition and motives behind long association with loyal employees may also be revealed. The following table includes factor loadings of statements that were loaded on to the first factor:

Table 4.3 shows the loadings of the five variables on the factor extracted. Loadings close to -1 or 1 indicate that the factor strongly influences the variable. Loadings close to 0 indicate that the factor weakly affects the variable. It can be inferred that "current state of HR decisions based on data analysis" (0.917), "dashboard access to bank managers for decision making" (0.879) and "revision and updation of HR policies on data analysis" (0.821) have significant positive loadings on Factor "Descriptive analytics". Therefore the factor describes the current state of HR decisions based on data analysis and access to different dashboards for decision-making.

Table 4.3: Factor loadings of statements under factor 1 ‘Descriptive analytics’

Statements	Factor loadings
This organization's current state of HR decisions are based on data analysis	.917
Bank managers' in this organization have access to different types of dashboards for decision making	.879
This organization’s HR policies are revised and updated on the basis of data analysis	.821
This organization use Data Analytics for learning why people stay in the organization	.738
This organization use Data Analytics for learning why people leave the organization	.714
Variance explained	26.67%
Reliability of the scale (Cronbach alpha)	.909
Source: Authors’ Calculation	

4.3.3 Factor 2: ‘Predictive analytics’

Findings of Exploratory Factor Analysis (EFA) produced three factors, and the second factor was named ‘Predictive analytics,’ which included five statements. ‘Predictive analytics’ was found to be the second most significant factor in terms of explaining variance in the data. The first factor explained 22.73% variance in the data. Findings highlighted that banks have been making predictions using historical data.

For instance, respondents agreed that banks had been increasingly using HR analytics for decision-making in the organization, such as workforce requirements and peak HR demand. Banks may also use HR analytics to identify individuals who need attention, leading to increased productivity and higher HR performance. Respondents agreed that banks often use HR analytics to determine which organizational function impacts the bottom line and to forecast performance levels.

The following table includes factor loadings of statements that were loaded on to the second factor:

Table 4.4: Factor loadings of statements under factor 2 ‘predictive analytics’

Statements	Factor loadings
Analytics is adequately used for decision-making in the organization	.873
This organization use data analytics for the identification of individuals who need attention	.816
This organization use data analytics for the identification of departments that need attention	.764
This organization use data analytics to determine which organizational function has most significant impact on the bottom line	.748
This organization uses data analytics to forecast performance levels	.692
Variance explained	22.73%
Reliability of the scale (Cronbach alpha)	.892
Source: Authors’ Calculation	

The above table 4.4 shows the loadings of the five variables on the factor extracted. Loadings close to -1 or 1 indicate that the factor strongly influences the variable. Loadings close to 0 indicate that the factor weakly affects the variable. It can be inferred that “adequate use of analytics for decision making” (0.873), “identification of individuals who needs attention using data analysis” (0.816), and “identification of departments requiring attention using data analysis” (0.764) have large positive loadings on Factor 2. Therefore “Predictive Analytics” describes the acceptable use of analytics for decision-making by identifying individuals and departments that needs attention.

4.3.4 Factor 3: ‘Prescriptive analytics’

Findings of Exploratory Factor Analysis (EFA) produced three factors, and the third factor was named ‘Prescriptive analytics’, which included four statements. The third most important factor in explaining variance in the data was found to be “Prescriptive analytics’. The factor was able to demonstrate a 20.85% variance in the data. Prescriptive analytics helps organizations to draw specific recommendations, and it

also helps to make informed decisions. Respondents agreed that the application of analytics had integrated use across the organization for HR functions, and the shift to data-based decisions has proved to be effective in their organizations. It was found that banks use HR analytics to monitor essential standards of organizational health and adapt the workforce to changes in a business environment.

The following table includes factor loadings of statements that were loaded on to the third factor:

Table 4.5: Factor loadings of statements under factor 3 ‘Prescriptive analytics’

Statements	Factor loadings
The application of analytics has integrated use across the organization for HR functions	.773
The shift to data-based decisions has proved to be effective in this organization	.749
This organization uses data analytics for monitoring key standards of organizational health	.673
This organization uses data analytics to adapt the workforce to changes in the business environment	.619
Variance explained	20.85%
Reliability of the scale (Cronbach alpha)	.821
Source: Authors’ Calculation	

The above table 4.5 shows the loadings of the four variables on the factor extracted. Loadings close to -1 or 1 indicate that the factor strongly influences the variable. Loadings close to 0 indicate that the factor weakly affects the variable. It can be inferred that “integrated use of analytics across organizations for HR functions” (0.773), “shift to data-based decisions proved effective” (0.749), and “monitoring key standards of organizational health using data analytics” (0.673) have significant positive loadings on Factor 2.

Therefore “Prescriptive Analytics” describes the integrated use of analytics for human resource functions, and the shift to data-based decisions proved effective.

Table 4.6: Result of Exploratory Factor Analysis

Factor	Reliability of Scale	Underlying variables	Variation explained
Descriptive analytics	.909	5	26.67%
Predictive analytics	.892	5	22.73%
Prescriptive analytics	.821	4	20.85%
Source: Authors' Calculation			

The rationale of analyzing the statements based on need for HR analytics through factor analysis was to quantify the degree to which each variable is associated with the factors and to obtain information about which factors contribute to performance on which variables.

It can be interpreted from Table 4.6 that there is a total of three factors bringing out the need of HR analytics in select banks. These factors are named '*Descriptive analytics*', '*Predictive analytics*', and '*Prescriptive analytics*'. "The organization's current state of HR decisions based on data analysis", "bank managers' access to different types of dashboards for decision making" and "organization's HR policies revised and updated based on data analysis" were substantially loaded on '*Descriptive analytics*'. Good use of analytics for decision making and organization use data analytics for identification of individuals need attention were substantially loaded on '*Predictive analytics*'. Finally, integrated use of analytics across the organization for HR functions and shift to data-based decisions were substantially loaded on '*Prescriptive analytics*'.

These studies support our findings (Alamelu et al., 2017; Fernandez et al., 2020; Alsuliman et al., 2021; Shet et al., 2021; Dhankar et al., 2022) Alamelu et al., 2017 based on factor analysis extracted seven factors such as self-efficacy, quantitative efficacy, data and tool availability, 'fear appeal, social influence, performance outcome and effort and level of acceptance as important factors of adaptability of HR analytics. The present study identifies three factors determining the need of HR analytics through factor analysis. Fernandez et al., 2020 identified factors such as

preparation; development, dissemination, and team enable the adoption of HR analytics.

Alsuliman et al., 2021 found the availability of tools as an essential factor impacting the decision to use HR analytics. With the framework synthesis method, Shet et al., 2021 stated that technological, organizational, environmental, data governance, and individual-related factors influence the adoption of HRA. Dhankar et al., 2022 validated the mediation model by exploring the relationship between technology readiness, adoption of human resources (HR analytics) by HR professionals and organizational career growth. The study findings validate the technology readiness model in the context of adopting HR analytics.

4.4 Objective 2: To study the role of HR Analytics on decision-making in HR functions

In the previous section, the present study applied EFA on 14 statements of HR analytics and the output produced three factors as under:

- Factor 1: ‘Descriptive analytics’
- Factor 2: ‘Prescriptive analytics’
- Factor 3: ‘Predictive analytics’

In this section, an attempt has been made to examine the influence of HR analytics on decision-making in HR functions using multiple linear regressions in SPSS. The regression analysis studies the dependence between variables. Dependence of one variable, called ‘dependent variable’ on other variables or variables called ‘independent variables’. It estimates the expected values of the dependent variable with the help of known values of the independent variable or variables. Multiple regression analysis analyzes the relationship between multiple independent variables and a single dependent variable. While extracting factors of HR analytics, the study saved factors as variables in SPSS. As a result, three new variables in SPSS were created, and these variables were taken as independent variables in the regression model.

The study developed four statements (Barney and Wright, 1998) for measuring manager’s perceptions of decision-making in HR functions. The mean score for these statements was calculated and used as a dependent variable in the regression model.

Therefore, mean score and standard deviations for statements measuring manager’s perceptions of decision-making in HR functions are given as under:

Table 4.7: Mean score for statements measuring decision making in HR functions

Statements	Mean score	Standard deviation
Overall, the HR department is performing its job the way it is expected to perform	4.35	1.034
The HR department has been able to meet expectations by executing its roles and responsibilities in a well defined manner	4.49	.996
I believe that HR department adds value to our business activities	4.29	.961
The HR department works in such a way that I would not like to see any change in its existing working style	4.44	.928
Overall mean	4.35	.64755
Source: Authors’ Calculation		

Findings (table 4.7) revealed that respondents had positive perceptions of all statements of decision-making in HR functions. The mean score for all statements was more significant than the scale mid value ‘3’. Managers of select banks agreed that the HR department is performing its job the way it is expected to perform. The HR department has met expectations by executing its roles and responsibilities well. These findings showed that HR departments in both public and private sectors have been performing well, and they are making decisions in the interest of their employees. Respondents believed that the HR department adds value to their business activities and that the department works in such ways that they would prefer to keep its existing working style the same

This finding indicated that employees in select banks are satisfied with the work of the HR department. The HR department has been assisting them to do business in a way that adds value to the bank’s operations. Overall, it can be interpreted that the HR department played a key role in making important decisions that help managers to streamline their work Further, to examine the influence of HR analytics on decision-making in HR functions, the present study developed a regression model given in equation 1.

The regression mentioned above equation may be presented using figure 4.3.

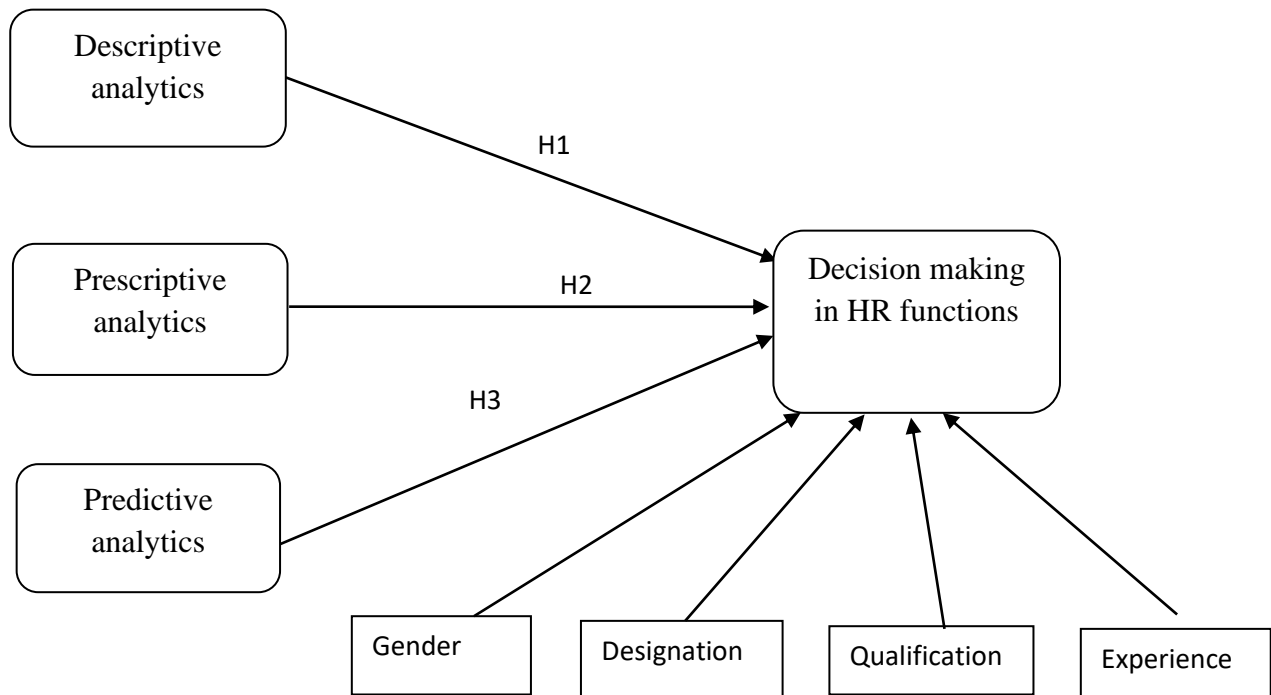


Figure 4.3: Role of HR analytics in decision making in HR functions

$$DM_i = a + b_1(Des_A_i) + b_2(Prs_A_i) + b_3(Pre_A_i) + e_i \quad (1)$$

Equation 1 describes the regression analysis.

where a = Intercept of regression line on y axis

b_i = Regression coefficient

DM = Decision-making in HR functions

Des_A = Descriptive analytics

Prs_A = Prescriptive analytics

Pre_A = Predictive analytics

The above figure reveals a diagrammatic presentation of the relationships proposed in the study. As per the above-mentioned figure, it is important to mention here that the study has considered four control variables that may potentially influence the dependent variable i.e. Decision making in HR functions. The control variables included in the model are: gender; designation of the respondents; qualification of the respondent and experience of the respondent. These variables were measured using nominal scale in the questionnaire. From above, it is evident that the study has proposed three hypotheses that can be used to test the relationship between three factors of HR analytics and decision-making in HR functions.

Therefore, the present investigation has drawn the following hypotheses:

- H1: The higher the intensity of using descriptive analytics in a bank, the greater the effectiveness of decision making in HR functions.
- H2: Higher the intensity of using prescriptive analytics in a bank, greater is the effectiveness of decision-making in HR functions.
- H3: Higher the intensity of using predictive analytics in a bank, greater is the effectiveness of decision-making in HR functions.

4.4.1 Testing multi-collinearity in regression equation

Multi-collinearity refers to high correlations among independent variables included in a regression equation. When two or more independent variables are used in a regression mode, it is advisable to check the presence of high correlation among them because multi-collinearity may render the regression coefficients inconsistent. Multi-collinearity can create severe issues in a predictive model because independent variables are significantly linked and may influence each other. In other words, it can be inferred that predictor variables are not independent and they have a significant association among them. Due to the high correlation among independent variables, the combined effect of independent variables on the outcome variable becomes inconsistent. Therefore, the study used Variance Inflation Factor (VIF) to examine the occurrence of multi-collinearity among independent variables included in the proposed model (Figure 4.2). The value of VIF indicates the severity of multi-collinearity in a regression model.

Table 4.8: Testing multi-collinearity in regression equation: Variance Inflation Factor

		Descriptive analytics	Prescriptive analytics	Predictive analytics
Correlations	Descriptive analytics	1.000	.000	.000
	Prescriptive analytics	.000	1.000	.000
	Predictive analytics	.000	.000	1.000
Significance value	Descriptive analytics	.	.500	.500
	Prescriptive analytics	.500	.	.500
	Predictive analytics	.500	.500	.
VIF		1.000	1.000	1.000
Source: Authors' Calculation				

When VIF is equal to '1', independent variables are not-correlated. When VIF lies between 1-10, it is inferred that predictor variables are moderately correlated. A value of VIF more significant than 10 indicates that predictor variables are highly correlated, causing biases in estimates.

Correlation values and corresponding VIF for the independent variables of the regression equation is given in the table 4.8.

Findings regarding multi-collinearity among independent variables indicated no significant correlation among the predictor variables included in the model, i.e. 'Descriptive analytics'; 'Prescriptive analytics'; and 'Predictive analytics'.

Furthermore, VIF for each predictor variable was found to be equal to '1', revealing that independent variables were not-correlated. This finding ruled out the possibility of multi-collinearity among independent variables.

4.4.2 Testing autocorrelation in the regression equation

Autocorrelation refers to the intensity of relationship between given time series values and lag values. It measures the relationship between a present value and the previous value of a variable. The presence of autocorrelation among variables of a regression model may be tested using Durbin-Watson statistic and its value varies from 0 to 4. A value of Durbin-Watson statistic equal to '2'; indicate that autocorrelation is not present in the variables, the value of the Durbin-Watson statistic from 0 to less than 2 indicate presence of positive autocorrelation- Durbin-Watson statistic from 2 to 4 shows negative autocorrelation among variables of the regression model. A rule of thumb regarding this test suggests that Durbin-Watson statistic ranging from 1.5 to 2.5, is relatively standard. However, its values outside the above range present a cause for concern for a regression model.

Table 4.9: Testing autocorrelation in regression equation: Durbin-Watson test

R	R Square	Durbin-Watson
.495 ^a	.245	1.658
F= 42.73; p< 0.000 (ANOVA test)		
Source: Authors' Calculation		

Findings of Durbin-Watson test (table 4.9) revealed that Durbin-Watson statistic is 1.658, between the acceptable ranges, i.e. 1.5 to 2.5. Therefore, the possibility of autocorrelation among variables of the regression model is ruled out. Further, findings revealed that HR analytics explained a 24.5% variation in decision-making in HR functions. Findings indicated that the overall impact of HR analytics on decision-making in HR functions was significant. The ANOVA table revealed that F value for this model was 42.73, which was significant at five percent significance level. From above, it is evident that the proposed regression model is free from two of the most-common issues, i.e. multi-collinearity; and autocorrelation. Therefore, the assumptions of linear regression have been examined that suggested going ahead with applying multiple linear regressions with the given data.

4.4.3 Testing homoscedasticity in the regression equation

While running a regression equation, the issue of homoscedasticity seems to be important as in the absence of homoscedasticity, the regression coefficients may be inconsistent. The homoscedasticity refers to the homogeneity of variance. In other words, it may be interpreted that homoscedasticity refers to the constant variance among error terms. In the presence of heteroscedasticity, the regression estimates often become invalid and interpretations based on these estimates are misleading. The presence of heteroscedasticity among error terms of a regression equation may be tested by examining the shape of a plot between standardized residual and standardized predicted variables. In SPSS, the plot between standardized residual and standardized predicted variables was obtained which is given as follows:

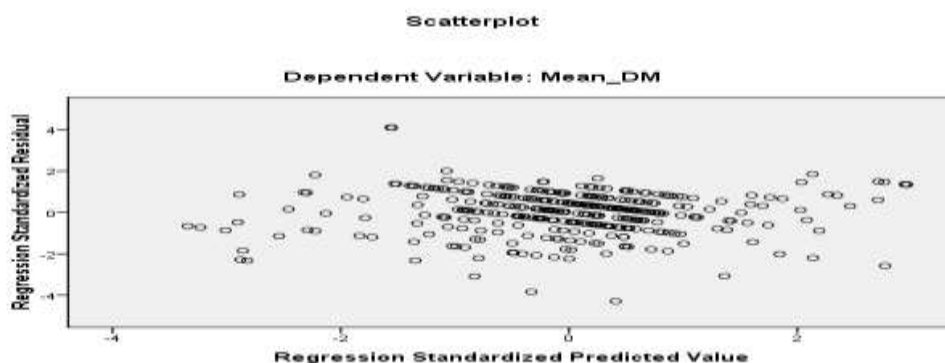


Figure 4.4: Scatterplot of testing homoscedasticity in the regression equation

The above plot reveals that there is a constant variance between standardized residual and standardized predicted variables of the model. There is no u-shaped or funnel shaped variance that may suggest inconsistent variance. The variance in the above-mentioned plot seems to be constant, which ruled out the possibility of presence of heteroscedasticity in the model.

From above, it is evident that the proposed regression model is free from three of the most-common issues i.e. multi-collinearity; autocorrelation and heteroscedasticity.

Therefore, the assumptions of linear regression have been examined that suggested going ahead with applying multiple linear regression with the given data.

4.4.4 Findings and discussion: Role of HR analytics in decision making in HR functions

The hypotheses mentioned in the previous section were tested using multiple regression in SPSS in which factors score of ‘Descriptive analytics’; ‘Prescriptive analytics’; and ‘Predictive analytics’ were taken as independent variables and mean of statements under ‘decision-making in HR functions’ was considered as the dependent variable. Regression analysis was applied on the given data in which enter method was used for putting independent variables in the regression equation.

Table: 4.10: Model Summary Regression

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.523 ^a	.274	.261	.5567
a. Predictors : (Constant) REGR factor score 3 for analysis 3, REGR factor score 2 for analysis 3, REGR factor score 3 for analysis 1 b. Dependent variable: Mean_DM				
Source: Authors' Calculation				

The model summary table represents the correlation value and the variance explained by the dependent factor on an independent element. The above Table 4.10 "R" value represents the correlation coefficient, and the r square value shows the variance explained. Table 4.10 provides R and R² values. The R-value represents the simple correlation and is .523, which indicates a positive relationship between Descriptive

Analytics, Predictive Analytics, and Prescriptive Analytics. The R denotes the strong relationship between the different variables. The value obtained from R is always positive. Therefore it explains how the regression equation fits in the observed data. The R^2 value is always measured between 0 and 1; with the constant term, the value of R-square obtained is .274. The value of R-square lies between 0 to 100%. The value (.274) suggests 27 % of the total variation in the dependent variable; the independent variables can explain. The coefficient of determination (R^2), is any change or variance in the dependent variable. The independent variable explains the proportion of variance, that is, descriptive, predictive, and prescriptive analytics.

Table 4.11: Table representing the Analysis of Variance

Model	Sum of Squares	Df	Mean Square	F	Sig.
Regression	45.823	7	6.546	21.122	.000 ^a
1 Residual	121.489	392	.310		
Total	167.311	399			
<p>a. Predictors : (Constant) REGR factor score 3 for analysis 3, REGR factor score 2 for analysis 3, REGR factor score 3 for analysis 1</p> <p>b. Dependent variable: Mean_DM</p>					
Source: Authors' Calculation					

Table 4.11 is the ANOVA table, which also shows the regression model and predicts the dependent variable. The ANOVA table represents the statistical significance of the regression model where the p-value is 0.00, which is less than 0.05, indicating that the regression model significantly predicts the outcome variable, i.e., it is a good fit for the data.

Table 4.12: Table represents the Unstandardized Coefficients of Decision Making in Human Resource Functions

Model	Unstandardized Coefficients		Standardized Coefficients	T	Sig.
	B	Std. Error	Beta		
Constant	3.309	.138		23.985	.000
Descriptive Analytics	.114	.028	.176	3.998	.000
Prescriptive Analytics	.156	.029	.241	5.441	.000
Predictive Analytics	.256	.028	.395	9.124	.000
Gender	.092	.029	.145	3.134	.002
Designation	.006	.028	.009	.198	.843
Qualification	.111	.058	.085	1.904	.058
Experience	.01	.031	.001	.028	.977
a. Dependent Variable: Mean_DM					
Source: Author's Calculation					

The coefficient table 4.12 provides the necessary information to predict human resource decision-making from the descriptive, predictive, and prescriptive analytics and determine whether independent variables contribute statically significantly to the model. Findings on the control variables suggested that these variables were having marginal impact on the decision-making in HR functions. As out of the four control variables inserted in the model, only one of them (gender) was found to have a significant influence on the decision-making in HR functions. Findings on control variables revealed following expressions:

$$\text{Decision making in HR function} = 3.309 + .145 (\text{Gender}) (\text{significant})$$

Decision making in HR function= 3.309 + .009 (Designation) (insignificant)

Decision making in HR function= 3.309 + .085 (Qualification) (insignificant)

Decision making in HR function= 3.309 + .001 (Experience) (insignificant)

The control variables such as designation, qualification and experience were found to have no impact on decision making in HR function. However, the influence of these variables was controlled so that findings of the give model become more efficient and valid.

Decision making in HR function= 3.309 + .114 (Descriptive Analytics)

The analysis depicts that, Descriptive Analytics significantly impact the decision-making in HR functions. Based on obtained data values, it is interpreted that Descriptive analytics leads to the effectiveness of decision-making in HR functions.

Decision making in HR function= 3.309 + .156 (Prescriptive Analytics)

The analysis depicts that Prescriptive Analytics significantly impact the decision-making in HR functions. Based on obtained data values, it is interpreted that Prescriptive analytics leads to decision-making effectiveness in HR functions.

Decision making in HR function= 3.309 + .256 (Predictive Analytics)

The analysis depicts that Predictive Analytics significantly impact the decision-making in HR functions. Based on obtained data values, it is interpreted that Predictive analytics leads to the effectiveness of decision-making in HR functions.

The factor-wise influence of HR analytics on decision-making in HR functions is given in the table 4.13.

Findings (table 4.13) indicated that all hypotheses proposed in the study were accepted as the factor-wise influence of factors of HR analytics on decision-making in HR functions was found to be significant. Descriptive analytics in a bank significantly influenced the effectiveness of decision-making in HR functions ($\beta = 0.176$; $p < 0.05$); thus, H1 was accepted.

Table 4.13: Role of HR analytics in decision making in HR functions

Hypotheses	Std. beta (β)	T	P	Decision (Accepted/Rejected)
H1: The higher the intensity of using descriptive analytics in a bank, the greater the effectiveness of decision making in HR functions.	.176	3.998	.000	Accepted
H2: Higher the intensity of using prescriptive analytics in a bank, greater is the effectiveness of decision-making in HR functions.	.241	5.441	.000	Accepted
H3: Higher the intensity of using predictive analytics in a bank, greater is the effectiveness of decision making in HR functions.	.395	9.124	.000	Accepted
Note: *significant at 5% level				
Source: Authors' Calculation				

It means that the higher the intensity of using descriptive analytics in a bank, the greater the decision-making effectiveness in HR functions. This finding suggested that the banks have been using descriptive analytics to take HR decisions based on data analysis and banks have access to different types of dashboards for decision making. It was found that banks often revise HR policies that are updated on the basis of data analysis. Banks were also found to use data analytics for learning why people stay in the organization and why people leave the organization.

Prescriptive analytics was found to be the second-most influential factor influencing the effectiveness of decision-making in HR functions ($\beta = 0.241$; $p < 0.000$), thereby, H2 was also accepted.

This finding suggested that prescriptive analytics in a bank plays a vital role in the effectiveness of decision-making in HR functions. It means that analytics has integrated use across organizations for HR functions, and the shift to data-based decisions has proved effective in this organization. Banks were also found to use data

analytics to monitor essential standards of organizational health and adapt the workforce to business environment changes.

From H3, it was expected that predictive analytics in a bank significantly influences the effectiveness of decision-making in HR functions. This hypothesis was supported as predictive analytics resulted in higher decision-making effectiveness in HR functions ($\beta = 0.395$; $p=0.01$). In addition, factors such as 'predictive analytics' were the strongest predictor of decision-making effectiveness in HR functions. This finding indicated that analytics is adequately used for decision-making in banks and banks use data analytics for the identification of individuals who need attention. Further, banks were also found to use data analytics to identify departments that need attention and determine which organizational function has the most significant impact on the bottom line.

These studies support our findings (Mishra et al., 2016; Ben-Gal 2019; Mohammed 2019; Pandey et al.,2022) Mishra et al., 2016 examined the application and impact of predictive analytics wherein author identified broader application in areas of human resource management. The study supported the potential of predictive analytics to achieve accuracy in decision-making for HR. Ben-Gal 2019 identified the implications of HR analytics trivial tasks and activities of human resource and practical implementation tools. For example, the tools which can yield high return on investment (ROI) in recruitment are predictive, training and development and retention, both descriptive and predictive yield a high return on investment. The present study also found significant use of predictive analytics in decision-making effectiveness in HR functions. Mohammed 2019 examined role of HR analytics in predictive decision-making. The author identifies the success of analytics-based intervention impacting predictive decision-making. Pandey et al., 2022 support the implications of HR analytics to assist managers in making predictive decisions.

4.5 Effect of various types of analytics on identified HR functions

The present study applied Exploratory Factor Analysis (EFA) on fourteen statements of HR analytics and the output produced three factors as under:

- Factor 1: 'Descriptive analytics'
- Factor 2: 'Prescriptive analytics'

- Factor 3: ‘Predictive analytics’

The present study has identified four major HR functions as given below:

- Recruitment
- Training and development
- Performance management
- Retention

The study developed fourteen (14) statements to measure each ‘recruitment’ and ‘training and development’ function; and twelve (12) statements were developed to measure ‘performance management’ and ‘employee retention’. Before examining the effect of various types of analytics on identified HR functions, the study applied Exploratory Factor Analysis (EFA) to the above statements so that factors under each HR function may be derived. The following sections contain analysis regarding Exploratory Factor Analysis (EFA) applied to identify HR functions.

4.5.1 Factors of recruitment in select banks

To apply Structural Equation Modeling, the study calculated the mean score and standard deviation for the recruitment function in the table below (4.14). Therefore, findings in regard to mean score and standard deviation for these statements are provided in the following table:

Table 4.14: Mean score and standard deviation for statements on recruitment in select banks

Sr. No.	Statements	Mean score	Standard deviation
1	This organization's HR executive are aware about number of vacancies for recruitment	4.85	1.221
2	This organization's human resource function maintains updated database for total manpower quantity recruited	4.91	1.228
3	This organization determines internal hiring rate (via promotion, transfer or other moves) in every recruitment cycle	4.79	1.306
4	This organization determines external hiring rate (employment agencies, advertisement, educational institutions) in every recruitment cycle	4.85	1.230
5	This organization minimizes time to recruit in each recruitment cycle	4.82	1.187
6	The applicants demonstrate adherence to ethical code during interview	4.66	1.245

7	This organization maintain higher offer acceptance rate in every recruitment cycle	4.63	1.103
8	This organization reduces cost of recruitment in every cycle	4.61	1.233
9	There is a system of tracking speed of hiring candidates in this organization	4.74	1.134
10	There is a system to identify ease of recruitment on basis of organizational roles (Assistant Manager, Deputy General Manager, Chief General Manager)	4.64	1.202
11	There is a system to identify difficulty of recruitment on basis of organizational roles (Assistant Manager, Deputy General Manager, Chief General Manager)	4.67	1.183
12	This organization determines cost for hiring the external employee in the company	4.65	1.262
13	This organization determines quality of recruits with their performance level	4.58	1.163
14	There is a system for tracking first year turnover in this organization	4.52	1.338
Source: Authors' Calculation			

Findings revealed that respondents agreed to the recruitment statements. Respondents agreed that human resource executives in their banks knows the vacancies and maintain an updated database for the total workforce required. Human resource managers in banks were found to have accurate information regarding internal and external hiring rates. HR managers in select banks were found to maintain higher offer acceptance rate in every recruitment cycle and attempt to reduce the recruitment cost in their organization. Banks were found to have a system of tracking speed of hiring candidates that help to identify ease of recruitment based on organizational roles.

4.5.1.1 Recruitment analytics for public and private sector banks

Examining the intensity of using various HR analytics in public and private sector banks is essential. Previous literature suggested that private sector banks have increasingly adopted the latest valuable technology and provided a more significant customer experience. For this, the mean score for all statements under recruitment analytics was compared for both public and private sector banks. Findings regarding comparing the use of recruitment analytics for public and private sector banks are given below:

Table 4.15: Recruitment analytics for public and private sector banks

Recruitment analytics	Mean	
	Public sector banks	Private sector banks
This organization's HR executive are aware about number of vacancies for recruitment	4.65	5.06
This organization's human resource function maintains updated database for total manpower quantity recruited	4.72	5.10
This organization determines internal hiring rate (via promotion, transfer or other moves) in every recruitment cycle	4.52	5.07
This organization determines external hiring rate (employment agencies, advertisement, educational institutions) in every recruitment cycle	4.61	5.09
This organization minimizes time to recruit in each recruitment cycle	4.59	5.06
The applicants demonstrate adherence to ethical code during interview	4.37	4.95
This organization maintain higher offer acceptance rate in every recruitment cycle	4.56	4.71
This organization reduces cost of recruitment in every cycle	4.47	4.76
There is a system of tracking speed of hiring candidates in this organization	4.59	4.89
There is a system to identify ease of recruitment on basis of organizational roles (Assistant Manager, Deputy General Manager, Chief General Manager)	4.59	4.70
There is a system to identify difficulty of recruitment on basis of organizational roles (Assistant Manager, Deputy General Manager, Chief General Manager)	4.65	4.70
This organization determines cost for hiring the external employee in the company	4.50	4.81
This organization determines quality of recruits with their performance level	4.53	4.64
There is a system for tracking first year turnover in this organization	4.31	4.73
Source: Authors' Calculation		

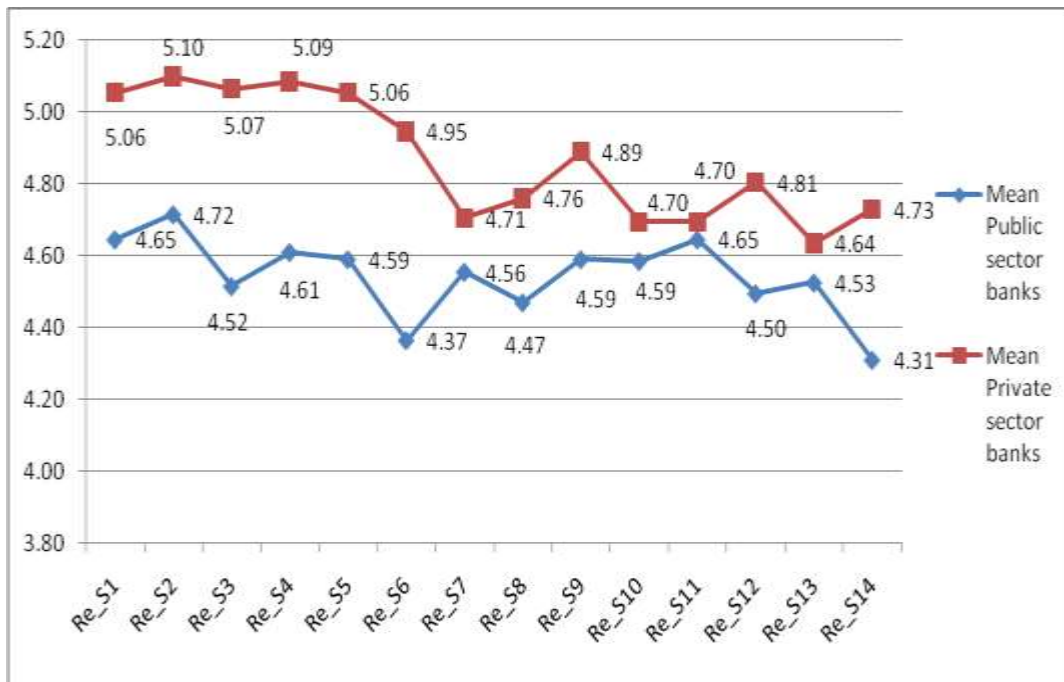


Figure 4.5: Recruitment in Public and Private Banks

It is evident from the findings mentioned above that private sector banks have outperformed public sector banks in terms of using recruitment analytics, as the mean score for all statements under recruitment analytics for private banks was found to be higher than the mean score of public sector banks. However, public sector banks in India are also challenging private banks in adopting and using the latest technology to enhance customer convenience and satisfaction. Therefore, the present study attempted to compare the difference in the use of recruitment analytics for public and private sector banks.

The study used two tests, KMO and Bartlett's Test of Sphericity, before applying EFA on fourteen (14) recruitment statements in select banks. First, sampling adequacy was examined using the KMO test.

This test suggests that the value of KMO varies from 0 to 1; a higher value of KMO (close to 1.0) implies that applying EFA on the given data is valid. Second, Bartlett's Test of Sphericity was used to examine correlation among variables. This test diagnoses the relatedness of the variables considered in the study and further throws light on detecting the factor structure. Findings of "KMO and Bartlett's Test" (refer to the table given above) highlighted that the value of KMO is 0.904, which is greater than the recommended value of 0.7 (Hair *et al.* 2006). Therefore, it was concluded

that the sample used in the study is adequate, which justifies the use of EFA on given data. Moreover, the chi-square value for Bartlett's Test of Sphericity was found to be 4592.63 and p-value for this test was less than 0.05 (level of significance). Findings of KMO and Bartlett's Test are given in the Table 4.16 below:

Table 4.16: “Findings of KMO and Bartlett's Test”

“Kaiser-Meyer-Olkin Measure of Sampling Adequacy”		.904
“Bartlett's Test of Sphericity”	“Approx. Chi-Square”	4592.63
	Degree of freedom	91
	“Sig. (p)”	.000
Source: Authors' Calculation		

This finding indicated the presence of a significant correlation among statements relating to bank recruitment. The findings of both KMO and Bartlett's Test were useful in concluding that the application of EFA on given data is justified. Figure 4.5 represents of Scree plot of Recruitment. Findings of EFA on 14 statements of recruitment in banks produced three factors as given below:

- Factor 1: Updated recruitment database
- Factor 2: Ease of recruitment
- Factor 3: Quality of recruitment

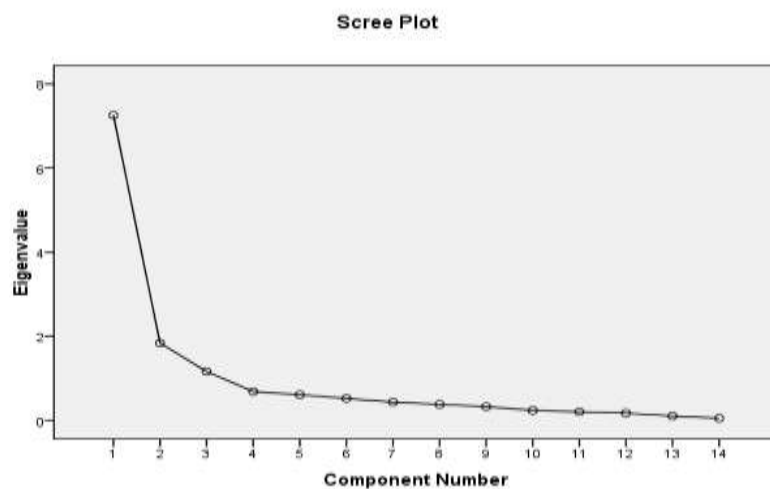


Figure 4.6: Scree plot of Recruitment

The first factor was named ‘updated recruitment database’, which included six statements. This factor was found to be the most significant factor in terms of explaining variance in the data. For instance, the first factor was able to explain 35.95% variance in the data. It was observed that respondents have positive perceptions of recruitment analytics being used in their organizations. Respondents believed that banks have been using HR analytics and HR managers are well aware about the future workforce requirements in their respective organizations, and they have been able to maintain an updated database for workforce requirements. In addition, It was found that banks attempt to minimize time to recruit in each recruitment cycle, and the applicants often demonstrate adherence to ethical code during interview. The following table includes factor loadings of statements that were loaded on the ‘updated recruitment database’:

Table 4.17: Factor loadings of statements under ‘updated recruitment database’

Statements	Factor loadings
This organization determines external hiring rate (employment agencies, advertisement, educational institutions) in every recruitment cycle	.917
This organization minimizes time to recruit in each recruitment cycle	.879
This organization determines internal hiring rate (via promotion, transfer or other moves) in every recruitment cycle	.821
This organization's HR executive are aware about number of vacancies for recruitment	.738
This organization's human resource function maintains updated database for total manpower quantity recruited	.714
The applicants demonstrate adherence to ethical code during interview	
Variance explained	35.95%
Reliability of the scale (Cronbach alpha)	.947
Source: Authors’ Calculation	

Findings of Exploratory Factor Analysis (EFA) on fourteen recruitment statements in select banks produced three factors, and the second factor was named ‘ease of recruitment’, which included six statements. This factor was found to be the second most significant factor in terms to explaining variance in the data. For instance, the first factor explained 21.87% variance in the data. In addition, findings highlighted

that banks maintained a higher offer acceptance rate, which helped reduce recruitment costs in every cycle. It was found that banks have installed a system for tracking the speed of hiring candidates in their organizations and determining cost for hiring the external employee in banks. The following table includes factor loadings of statements that were loaded on to ‘ease of recruitment’. Findings of Exploratory Factor Analysis (EFA) on fourteen statements on recruitment in select banks produced three factors. The third factor was named ‘quality of recruitment’, which included two words. This factor was found to be the third most significant factor in terms of explaining variance in the data. For instance, the first factor explained a 15.46% variance in the data. In addition, it was found that using analytics in banks helps to determine the quality of recruits with their performance level, and banks have a system for tracking first-year turnover in their organizations.

Table 4.18: Factor loadings of statements under ‘ease of recruitment’

Statements	Factor loadings
There is a system to identify difficulty of recruitment on basis of organizational roles (Assistant Manager, Deputy General Manager, Chief General Manager)	.823
This organization determines cost for hiring the external employee in the company	.809
There is a system to identify ease of recruitment on basis of organizational roles (Assistant Manager, Deputy General Manager, Chief General Manager)	.672
There is a system of tracking speed of hiring candidates in this organization	.578
This organization maintain higher offer acceptance rate in every recruitment cycle	.563
This organization reduces cost of recruitment in every cycle	.525
Variance explained	21.87%
Reliability of the scale (Cronbach alpha)	.857
Source: Authors’ Calculation	

Structural Equation Modeling through AMOS has been used to analyze the effects of Descriptive, Predictive, and Prescriptive analytics on updated recruitment databases, ease of recruitment and quality of recruitment. Hypothesized relationships are presented through path diagrams in structural equation modeling. Figure 4.6 shows

the relationship between HR analytics and recruitment. It consists of three exogenous variables, ‘Descriptive analytics’, ‘Predictive analytics’ and ‘Prescriptive analytics’ and three endogenous variables, ‘updated recruitment database’, ‘ease of recruitment’ and ‘quality of recruitment’ as endogenous variables. The following table includes factor loadings of statements that were loaded on to third factor.

Table 4.19: Factor loadings of statements under ‘quality of recruitment’

Statements	Factor loadings
There is a system for tracking first year turnover in this organization	.892
This organization determines quality of recruits with their performance level	.787
Variance explained	15.46%
Reliability of the scale (Cronbach alpha)	.775
Source: Authors’ Calculation	

4.5.1.2 Effect of various types of HR analytics on recruitment

The path diagram shows the dependence of an updated recruitment database, ease of recruitment and quality of recruitment on descriptive, predictive, and Prescriptive analytics. From the findings of previous sections, it was clear that the study identified three types of HR analytics and three factors of recruitment in banks, as given under:

Table 4.20: Identification of Factors

Types of HR analytics	Factors of recruitments
Descriptive analytics	Updated recruitment database
Prescriptive analytics	Ease of recruitment
Predictive analytics	Quality of recruitment

The study proposed nine relationships between factors of HR analytics and recruitments in banks, as mentioned in the table 4.21.

Table 4.21: Hypotheses proposed to examine the effect of various types of HR analytics on recruitments in banks

Sr. No.	Proposed hypotheses	Relationship
H1	Higher the use of descriptive analytics; more-updated is the recruitment database in select banks	DA → RDB (+)
H2	Higher the use of descriptive analytics; easier is the recruitment in select banks	DA → EoR (+)
H3	Higher the use of descriptive analytics; greater is the quality of recruitment in select banks	DA → QoR (+)
H4	Higher the use of prescriptive analytics; more-updated is the recruitment database in select banks	Pres_A → RDB (+)
H5	Higher the use of prescriptive analytics; easier is the recruitment in select banks	Pres_A → EoR (+)
H6	Higher the use of prescriptive analytics; greater is the quality of recruitment in select banks	Pres_A → QoR (+)
H7	Higher the use of predictive analytics; more-updated is the recruitment database in select banks	Pred_A → RDB (+)
H8	Higher the use of predictive analytics; easier is the recruitment in select banks	Pred_A → EoR (+)
H9	The higher the use of predictive analytics; greater is the quality of recruitment in select banks	Pred_A → QoR (+)
Note: DA: descriptive analytics; RDB: recruitment database; EoR: ease of recruitment; QoR: quality of recruitment; Pres_A: prescriptive analytics; Pred_A: predictive analytics.		
Source: Authors' Calculation		

The '+' sign in the above table shows a positive linear relationship among variables. Based on these hypotheses, the current study established a conceptual model, shown in the accompanying figure. In addition, the measurement model was also subjected to confirmatory factor analysis (CFA), and the model's validity and reliability were investigated.

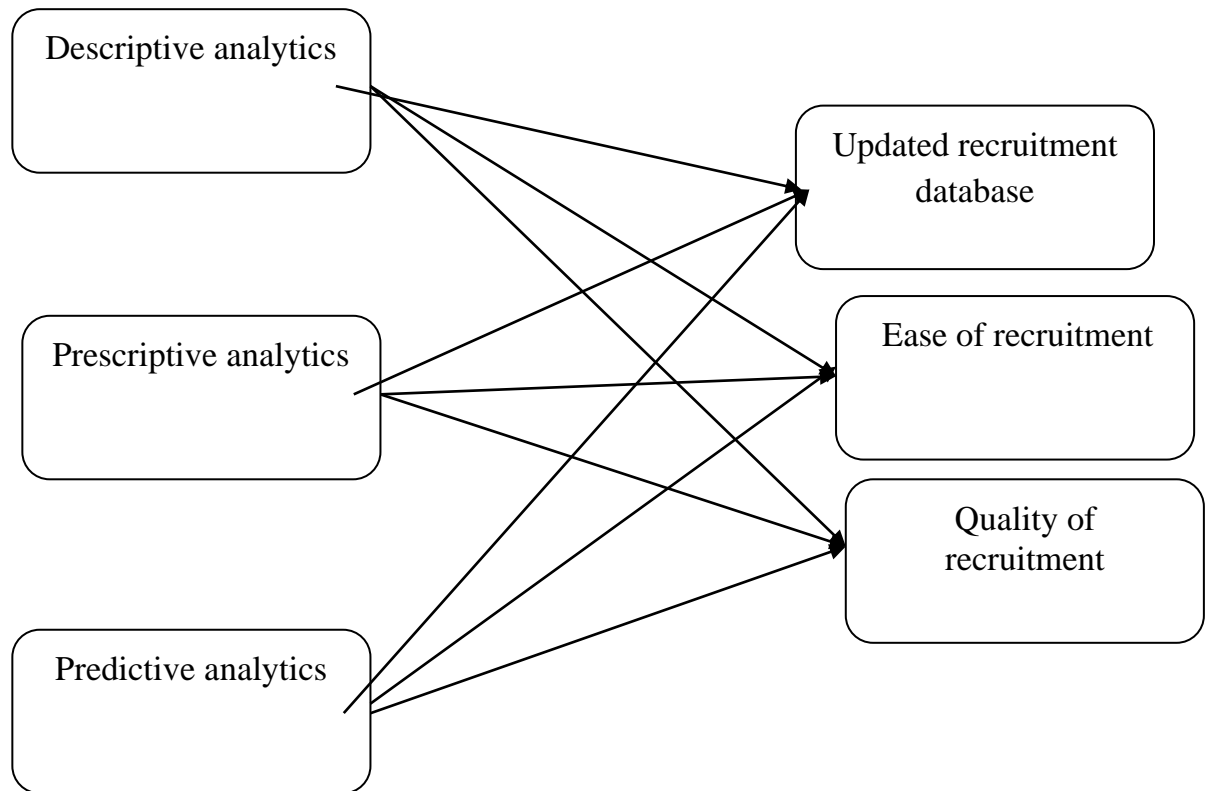


Figure 4.7: The conceptual model for examining the effect of various types of HR analytics on recruitments in select banks

4.5.1.3 Testing measurement model ‘the effect of various types of HR analytics on recruitments in banks

The measurement model was tested for both reliability and validity. The statistics pertaining to reliability and validity were obtained using confirmatory factor analysis (CFA) in AMOS.

4.5.1.4 Reliability of the constructs:

A construct is reliable if it generates similar results over time, given that measurement conditions remain the same. The constructs’ reliability in the model was tested with the help of ‘composite reliability’, denoted by CR in the table below. Composite reliability (CR) for each construct was more significant than 0.70, a minimum cut-off value for constructs to be reliable (Nunnally, 1978). Therefore, it is concluded that the constructs used in the measurement model were reliable.

4.5.1.5 Validity of the constructs:

The validity of a construct refers to the degree to which a construct measures what it is supposed to measure. The present study tested two types of validity: convergent

and discriminant. First, **convergent validity** refers to the degree to which two or more measures used in a construct are related to each-other. The findings revealed that average variance extracted (AVE) for each construct was more significant than 0.5, the minimum cut-off value for a construct to have convergent validity (Fornell & Larcker, 1981). These findings established the convergent validity of the constructs used in the study. Second, **discriminant validity** conceptualizes that constructs used in a study differ significantly.

Table 4.22: Statistics showing reliability and validity of the model

	CR	AVE	EoR	DA	Pred_A	Pres_A	RDB	QoR
EoR	0.858	0.505	0.710					
DA	0.856	0.549	0.056	0.741				
Pred_A	0.845	0.522	0.012	0.433	0.722			
Pres_A	0.812	0.545	0.013	0.477	0.343	0.738		
RDB	0.952	0.771	0.513	0.012	0.034	0.037	0.878	
QoR	0.825	0.712	0.534	0.057	0.013	0.076	0.484	0.844
Note: DA: descriptive analytics; RDB: recruitment database; EoR: ease of recruitment; QoR: quality of recruitment; Pres_A: prescriptive analytics; Pred_A: predictive analytics.								
CR represents composite reliability; and AVE represents Average variance extracted								
Source: Authors' Calculation								

Table 4.23: Fit indices of the measurement model ‘the effect of various types of HR analytics on recruitments in banks’

Sr. No.	Indices with value	Recommended value	Reference
1	Chi-square=850.55, $p < 0.001$; dof=331; chi-square/dof=2.57	chi-square/dof < 3	Hair et al., 2006
2	Goodness of fit (GFI) = 0.868	GFI > 0.8	Baumgartner & Homburg, 1996
3	Comparative Fit Index (CFI) = 0.927	CFI > 0.9	Hair et al. 2006
4	Tucker-Lewis Index (TLI) = 0.917	TLI > 0.9	Hair et al. 2006
5	Root Mean Square Error of Approximation (RMSEA) = 0.063	RMSEA < 0.08	Steiger, 1990
Note: dof: degrees of freedom			
Source: Authors' Calculation			

For example, in Table 4.22, diagonal values are the square root of AVE, and off-diagonal values represent values of pairwise correlations among respective constructs. The correlations between constructs (off-diagonal values) were less than the square root of AVE (diagonal values).

These findings supported the discriminant validity of the constructs used in the model. Moreover, every item under a specific construct was found to have factor loading greater than 0.5 (Fornell & Larcker, 1981). This finding reveals that there is convergent validity among the scales used. The model fit indices results indicate an acceptable fit of the measurement model as various statistics supported fit of the measurement model, as given in the table 4.23. Findings highlighted that the statistics given in the Table 4.23 above meet the specified criteria given by different authors. Therefore, the present measurement model is an adequately fit.

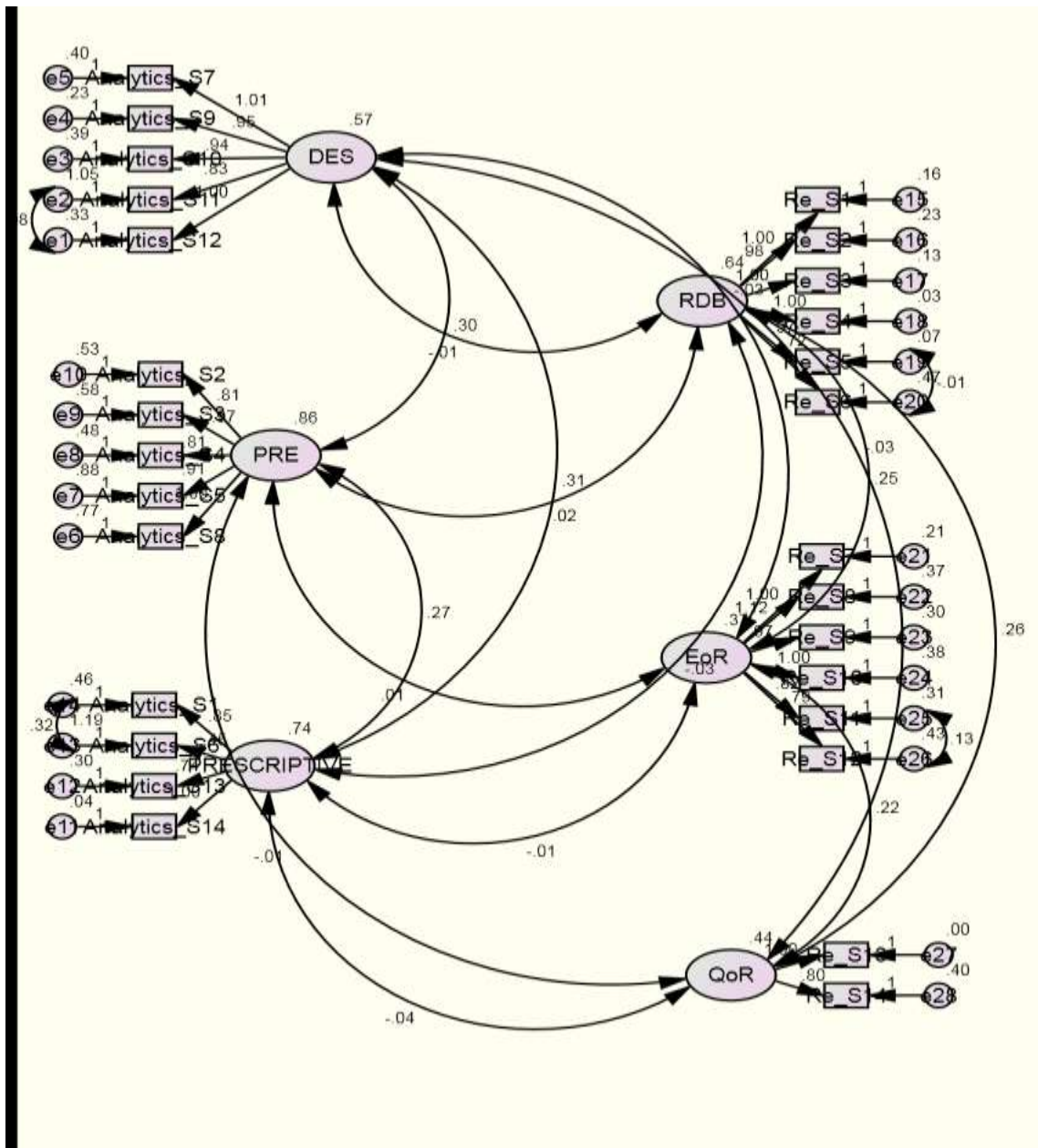


Figure 4.8: The path diagram for the hypothesized relationship of descriptive analytics, predictive analytics and prescriptive analytics and updated recruitment database, ease of recruitment, and quality of recruitment

4.5.1.6 Testing structural model ‘the effect of various types of HR analytics on recruitments in banks’

The present study proposed nine hypotheses to examine the effect of various types of HR analytics on bank recruitment. These hypotheses were empirically tested with the

help of Structural Equation Modeling. The findings of standardized parameter estimates are provided in the following table 4.24.

Table 4.24: Results of the structural model

Sr . No.	Proposed hypotheses	Relationship	Estimate (β)	t value	p value
H3	Higher the use of descriptive analytics; more-updated is the recruitment database in select banks	DA → RDB (+)	0.265	7.483	0.000*
H4	Higher the use of descriptive analytics; easier is the recruitment in select banks	DA → EoR (+)	0.307	10.1	0.000*
H5	Higher the use of descriptive analytics; greater is the quality of recruitment in select banks	DA → QoR (+)	0.010	0.301	0.763
H6	Higher the use of prescriptive analytics; more-updated is the recruitment database in select banks	Pres_A → RDB (+)	0.576	13.034	0.000*
H7	Higher the use of prescriptive analytics; easier is the recruitment in select banks	Pres_A → EoR (+)	0.598	16.003	0.000*
H8	Higher the use of prescriptive analytics; greater is the quality of recruitment in select banks	Pres_A → QoR (+)	0.103	0.398	0.690
H9	Higher the use of predictive analytics; more-updated is the recruitment database in select banks	Pred_A → RDB (+)	0.179	4.324	0.000*
H10	Higher the use of predictive analytics; easier is the recruitment in select banks	Pred_A → EoR (+)	0.197	5.691	0.000*
H11	Higher the use of predictive analytics; greater is the quality of recruitment in select banks	Pred_A → QoR (+)	0.020	0.353	0.724
* Significant at 5 percent level of significance.					
Notes: DA: descriptive analytics; RDB: recruitment database; EoR: ease of recruitment; QoR: quality of recruitment; Pres_A: prescriptive analytics; Pred_A: predictive analytics.					
Source: Authors' Calculation					

The results of the model are used to examine the hypothesized relationship between variables: Descriptive analytics and updated recruitment database; descriptive analytics and ease of recruitment; descriptive analytics and quality of recruitment; predictive analytics and updated recruitment database; predictive analytics and ease of recruitment; predictive analytics and quality of recruitment; prescriptive analytics and

updated recruitment database; prescriptive analytics and ease of recruitment; prescriptive analytics and quality of recruitment.

H3: Higher the use of descriptive analytics; more-updated is the recruitment database in select banks

The connecting path between descriptive analytics and the updated recruitment database yields Beta value= 0.265, Critical ratio=7.483, which is statistically significant as P-value <0.05, which means higher the use of descriptive analytics; more-updated is the recruitment database in select banks. Thus, H3 is accepted. This finding indicated that descriptive analytics helps banks determine external hiring rates for different recruitment sources such as employment agencies, advertisement and educational institutions, etc. Similarly, internal hiring rate for different recruitment sources, such as promotions and transfers, can also be determined using descriptive analytics in banks. Furthermore, descriptive analytics helped banks minimize the recruitment time for each recruitment cycle and made the HR executives more aware of the number of vacancies available. Therefore, the total human resources required for the whole organization can be assess using descriptive analytics. Based on these findings, banks are suggested using descriptive analytics to:

- Determine external hiring rate
- Determine the internal hiring rate
- Minimize the recruitment time
- Determine total man-power required

H4: Higher the use of descriptive analytics; easier is the recruitment in select banks

The connecting path between descriptive analytics and ease of recruitment yields a Beta value= 0.307, Critical ratio=10.1, which is statistically significant as P-value <0.05, which means higher the use of descriptive analytics, the easier is the recruitment in select banks. Thus, H4 is accepted. This finding indicated that using descriptive analytics helps banks identify the recruitment requirement for various organizational roles such as assistant manager, deputy general manager, and chief general manager, etc. The cost of hiring external employee in the banks can be

identified by using descriptive analytics that can be used for tracking speed of hiring candidates in banks. The adoption of descriptive analytics in banks was also found to be helpful in maintaining a higher offer acceptance rate that reduces the cost of recruitment in every cycle.

Therefore, banks are suggested to use descriptive analytics to:

- Identify the recruitment requirement
- Track the speed of hiring candidates
- Maintain higher offer acceptance
- Reduce the cost of recruitment

H5: Higher the use of descriptive analytics; greater is the quality of recruitment in select banks

The connecting path between descriptive analytics and quality of recruitment yields Beta value= 0.010, Critical ratio=0.301, which is statistically not significant as P-value > 0.05 which means Higher the use of descriptive analytics; less is the quality of recruitment in select banks. Thus, H5 is not accepted.

H6: Higher the use of prescriptive analytics; more-updated is the recruitment database in select banks

The connecting path between prescriptive analytics and updated recruitment database yields Beta value= 0.576, Critical ratio=13.034, which is statistically significant as P-value <0.05, which means higher the use of prescriptive analytics; a more-updated recruitment database in select banks. Thus, H6 is accepted. These findings suggested banks adopt prescriptive analytics so that recruitment database in banks can be updated as desired.

The banks need to focus on the integrating analytics for various HR functions to take data based decisions effectively. Further, banks also need to adopt prescriptive analytics so that essential standards of organizational health can be maintained and the changes in the workforce can be assessed.

H7: Higher the use of prescriptive analytics; easier is the recruitment in select banks

The connecting path between prescriptive analytics and ease of recruitment yields Beta value= 0.598, Critical ratio=16.003, which is statistically significant as P-value <0.05 which means higher the use of prescriptive analytics; easier is the recruitment in select banks. Thus, H7 is accepted. This finding suggested that banks must adopt prescriptive analytics to make recruitment easier. In addition, it was found that when prescriptive analytics is used for various banking functions, it helps to determine the cost of hiring the external employees and to track speed of hiring candidates.

H8: Higher the use of prescriptive analytics; greater is the quality of recruitment in select banks

The connecting path between prescriptive analytics and quality of recruitment yields a Beta value= 0.103, Critical ratio=0.398, which is statistically insignificant as P-value > 0.05 which means higher the use of prescriptive analytics; less is the quality of recruitment in select banks. Thus, H8 is not accepted.

H9: Higher the use of predictive analytics; more-updated is the recruitment database in select banks

The connecting path between predictive analytics and updated recruitment database yields Beta value= 0.179, Critical ratio=4.324, which is statistically significant as P-value < 0.05 which means higher the use of predictive analytics, a more-updated recruitment database in select banks. Thus, H9 is accepted. This finding suggested that banks use predictive analytics so that recruitment database can be updated. Predictive analytics seems to be helpful in minimizing the recruitment time and making HR managers more aware of the number of vacancies available in banks. In addition, when predictive analytics is used during banking recruitment, candidates are more likely to adhere to ethical code of conduct during recruitment process.

H10: Higher the use of predictive analytics; easier is the recruitment in select banks

The connecting path between predictive analytics and ease of recruitment yields Beta value= 0.197, Critical ratio=4.324, which is statistically insignificant as P-value <0.05, which means higher the use of predictive analytics; the easier recruitment in select banks. Thus, H10 is accepted. Based on this finding, banks are suggested to use predictive analytics to take effective decisions. For example, the predictive analytics can identify employees needing more attention to improve their organizational performance. Further, underperforming banking departments can also be identified using predictive analytics. Predictive analytics was found to be useful for banks from multiple perspectives. For instance, it can be adopted by banks to determine the banking functions needing more focus and to forecast employee performance levels with respect to their designation, branch and location.

H11: Higher the use of predictive analytics; greater is the quality of recruitment in select banks

The connecting path between predictive analytics and quality of recruitment yields Beta value= 0.020, Critical ratio=0.353, which is statistically insignificant as P-value > 0.05 which means higher the use of predictive analytics; less is the quality of recruitment in select banks. Thus, H11 is not accepted.

4.5.2 Factors of training and development in select banks

The study calculated mean score and standard deviation on factors of training and development in select banks (refer to Table 4.25) for applying Structural Equation Modeling.

Table 4.25: Mean score and standard deviation for statements on training and development in select banks

Sr. No.	Statements	Mean score	Standard deviation
1	There is a system to track the duration of annual training hours undergone by employee	4.54	1.307
2	This organization ascertains expenditure per employee on training and development	4.45	1.374
3	This organization adopts initiatives for identification of priority skills gap	4.41	1.506
4	This organization invest in training as a proportion of profit earned in a year	4.52	1.234
5	This organization invests in training as a proportion of payroll provided in a year	4.48	1.159
6	This organization invests in training as a percentage of revenue in a year	4.53	1.210
7	This organization ascertains percentage of employees receiving training every year	4.53	1.154
8	This organization ascertains percentage of employees with competency development plans in a branch	4.48	1.174
9	A quantifiable measure to track learners' activity and value from training program is deployed by this organization	4.76	1.555
10	This organization keeps track of instances of misconduct resulting from inadequate training	4.55	1.558
11	This organization keeps a track of effectiveness of training programs	4.66	1.389
12	A system for measuring participant satisfaction levels with training activities is deployed by organization	4.63	1.424
13	This organization determines improvement in performance post-training in each cycle	4.56	1.492
14	This organization determines effectiveness of quality improvement post training in each cycle	4.61	1.637
Source: Authors' Calculation			

Findings regarding the mean score and standard deviation for these statements are given in the following table. Findings revealed that respondents agreed with the training and development statements. Respondents agreed that there is a system to track the duration of annual training hours under which bank employees have gone. Banks were found to have data regarding the expenditure per employee incurred on training and development activities and have adopted initiatives to identify priority skills gaps among employees. It was found that banks have successfully invested in training as a proportion of profit earned in a year and training as a proportion of payroll provided in a year. Banks were also found to have access to data regarding

investments in training as a percentage of revenue in a year and the percentage of employees receiving training every year. Banks were found to keep track of instances of misconduct resulting from inadequate training and of the effectiveness of training programs. Organizations and banks deploy employee satisfaction regarding training activities and determine performance improvement post-training in each cycle.

4.5.2.1 Training and development analytics for public and private sector banks

Examining the intensity of using various HR analytics in public and private sector banks is essential. Therefore, the present study compared the difference training and development analytics use by public and private sector banks.

Table 4.26: Training and development analytics for public and private sector banks

Training and development analytics	Mean	
	Public sector banks	Private sector banks
There is a system to track the duration of annual training hours undergone by employee	4.35	4.74
This organization ascertains expenditure per employee on training and development	4.28	4.63
This organization adopts initiatives for identification of priority skills gap	4.24	4.59
This organization invest in training as a proportion of profit earned in a year	4.29	4.74
This organization invests in training as a proportion of payroll provided in a year	4.29	4.67
This organization invests in training as a percentage of revenue in a year	4.34	4.72
This organization ascertains percentage of employees receiving training every year	4.39	4.67
This organization ascertains percentage of employees with competency development plans in a branch	4.33	4.62
A quantifiable measure to track learners' activity and value from training program is deployed by this organization	4.52	5.01
This organization keeps track of instances of misconduct resulting from inadequate training	4.25	4.86
This organization keeps a track of effectiveness of training programs	4.39	4.93
A system for measuring participant satisfaction levels with training activities is deployed by organization	4.34	4.92
This organization determines improvement in performance post-training in each cycle	4.22	4.91
This organization determines effectiveness of quality improvement post training in each cycle	4.36	4.86
Source: Authors' Calculation		

The mean scores for all statements under training and development analytics were compared for public and private sector banks. Findings regarding comparing the use of training and development analytics for public and private sector banks are given in Table 4.26. It is evident from the findings mentioned above that private sector banks have outperformed public sector banks in terms of using training and development analytics, as the mean score for all statements under training and development analytics for private banks was found to be higher than the mean score of public sector banks.

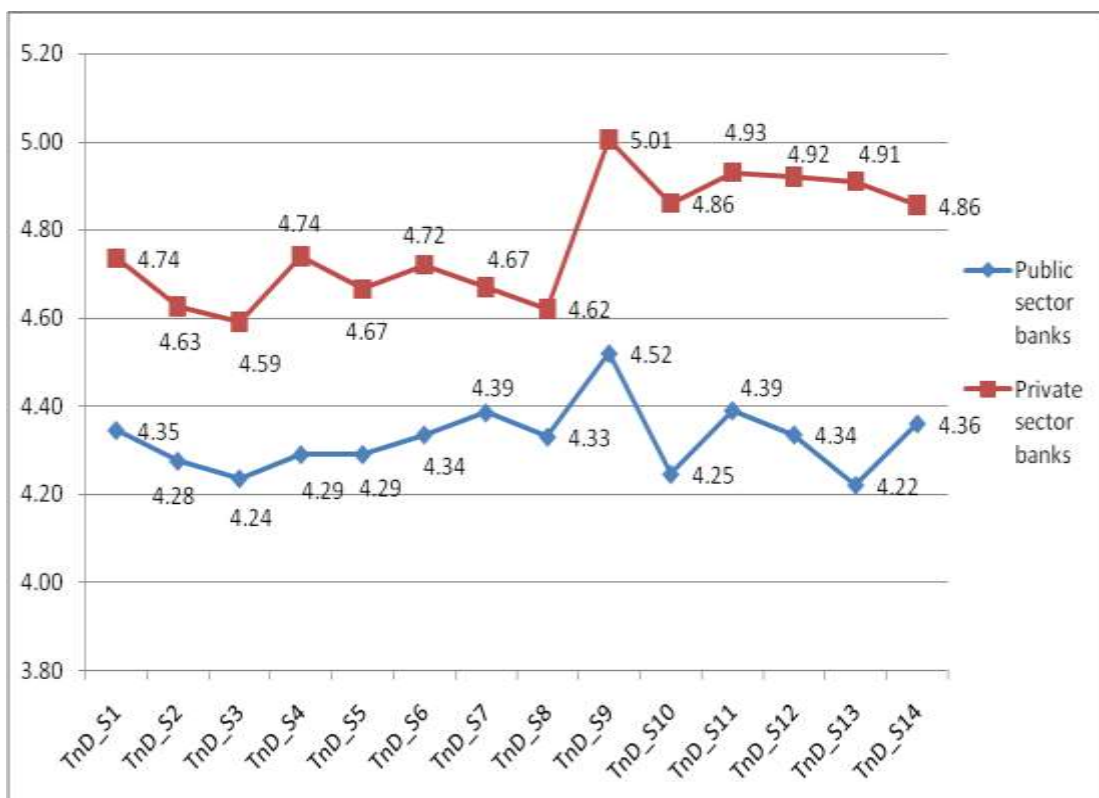


Figure 4.9: Training and Development in Public and Private Banks

Further, the study used KMO and Bartlett's Test of Sphericity before applying EFA on 14 statements of training and development in select banks. First, sampling adequacy was examined using the KMO test. This test suggests that the value of KMO varies from 0 to 1; a higher value of KMO (close to 1.0) implies that applying EFA on the given data is valid. Second, Bartlett's Test of Sphericity was used to examine presence of correlation among variables.

Findings of KMO and Bartlett's Test are given in the table below.

Table 4.27 “Findings of KMO and Bartlett's Test”

“Kaiser-Meyer-Olkin Measure of Sampling Adequacy”		.833
“Bartlett's Test of Sphericity”	“Approx. Chi-Square”	4146.11
	Degree of freedom	91
	“Sig. (p)”	.000
Source: Authors’ calculation		

This test diagnoses relatedness of the variables considered in the study and further throws light on detecting the factor structure. Findings of “KMO and Bartlett's Test” (refer to the table 4.27 given above) highlighted that value of KMO 0.833, which is greater than the recommended value of 0.7 (Hair *et al.*, 2006). Therefore, it was concluded that the sample used in the study is adequate, which justifies using of EFA on given data. Moreover, chi-square value for Bartlett's Test of Sphericity was found to be 4146.11 and p value for this test was less than 0.05 (level of significance). The finding indicated the presence of significant correlation among statements relating to bank training and development. Figure 4.9 represents scree plot of T&D. The findings of both KMO and Bartlett's Test were useful in concluding that applying EFA on given data is justified. Findings of EFA on 14 statements of training and development in banks produced three factors as given below:

- Factor 1: Post training analytics
- Factor 2: Financial analytics of training
- Factor 3: Training for skill-gap identification

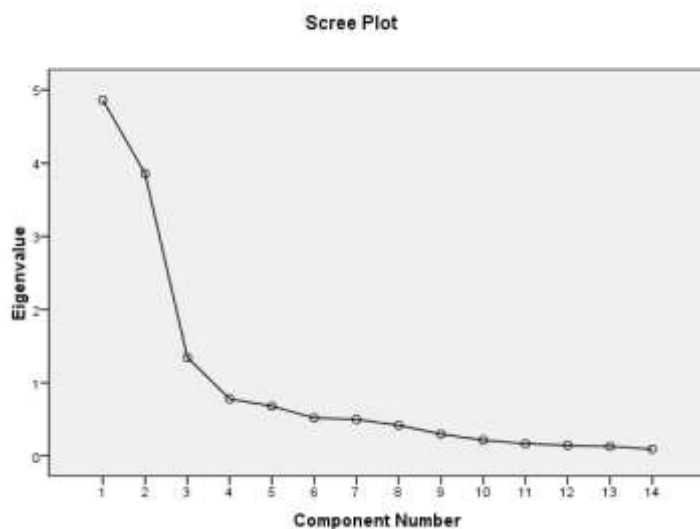


Figure 4.10: Scree plot of Training and Development

The first factor was ‘post-training analytics’, which included six statements. This factor was found to be most significant factor in terms of explaining variance in the data. For instance, the first factor was able to explain a 30.89% variance in the data. It was observed that respondents have positive perceptions of post-training analytics being used in their organizations. Respondents believed that banks have been using HR analytics to keep records of post training parameters such as misconduct resulting from inadequate training; effectiveness of training programs; improvement in performance; and quality improvement post training in each cycle. The table 4.28 includes factor loadings of statements that were loaded on ‘post training analytics’: Findings of EFA on 14 statements on training and development in select banks produced three factors, and second factor was named ‘financial analytics of training’, which included five statements.

Table 4.28: Factor loadings of statements under ‘post training analytics’

Statements	Factor loadings
This organization keeps track of instances of misconduct resulting from inadequate training	.898
This organization determines improvement in performance post-training in each cycle	.895
This organization keeps a track of effectiveness of training programs	.891
A system for measuring participant satisfaction levels with training activities is deployed by organization	.886
A quantifiable measure to track learners' activity and value from training program is deployed by this organization	.788
This organization determines effectiveness of quality improvement post training in each cycle	.666
Variance explained	30.89%
Reliability of the scale (Cronbach alpha)	.915
Source: Authors' Calculation	

The table 4.29 includes factor loadings of statements that were loaded onto ‘financial analytics of training’:

Table 4.29: Factor loadings of statements under ‘financial analytics of training’

Statements	Factor loadings
This organization invests in training as a proportion of payroll provided in a year	.915
This organization invest in training as a proportion of profit earned in a year	.914
This organization invests in training as a percentage of revenue in a year	.873
This organization ascertains percentage of employees receiving training every year	.831
This organization ascertains percentage of employees with competency development plans in a branch	.761
Variance explained	28.04%
Reliability of the scale (Cronbach alpha)	.922
Source: Authors’ Calculation	

This factor was found to be the second most significant factor in terms of explaining variance in the data. For instance, the first factor was able to explain 28.04% variance in the data. Findings highlighted that banks have been able to invest in training for their employees as a proportion of profit earned in a year and as a proportion of payroll provided in a year. Banks also invested in training as a percentage of revenue in a year and ascertained a percentage of employees with competency development plans in a branch. Findings of EFA on 14 statements on training and development in select banks produced three factors. The third factor was 'training for skill-gap identification', which included three statements. This factor was found to be the third most significant factor in terms of explaining variance in the data. For instance, the first factor was able to explain a 12.92% variance in the data. It was found that the use of analytics in banks helps to track the duration of annual training hours undergone by the employee, to assess expenditure per employee on training and development and to adopt initiatives for the identification of priority skills gap. The following table 4.30 includes factor loadings of statements that were loaded onto third factor, 'training for skill-gap identification':

Table 4.30: Factor loadings of statements under 'training for skill-gap identification'

Statements	Factor loadings
This organization ascertains expenditure per employee on training and development	.778
This organization adopts initiatives for identification of priority skills gap	.764
There is a system to track the duration of annual training hours undergone by employee	.688
Variance explained	12.92%
Reliability of the scale (Cronbach alpha)	.642
Source: Authors' Calculation	

4.5.2.2 Effect of various types of HR analytics on training and development

From the findings of previous sections, it was clear that the study identified three types of HR analytics and three factors of training and development in banks, as given under:

Table 4.31 Identification of Factors

Types of HR analytics	Factors of training and development
Descriptive analytics	Post training analytics
Prescriptive analytics	Financial analytics of training
Predictive analytics	Training for skill-gap identification

Structural Equation Modeling through AMOS has been used to analyze effects of descriptive, predictive, predictive, and Prescriptive analytics on post-training analytics, financial analytics of training and training for skill-gap identification.

Table 4.32 Hypotheses proposed to examine the effect of various types of HR analytics on training and development in banks

Sr. No.	Proposed hypotheses	Relationship
H12	Higher the use of descriptive analytics; greater is the use of post training analytics in select banks	DA → PTA (+)
H13	Higher the use of descriptive analytics; greater is the use of financial analytics of training in select banks	DA → FAT (+)
H14	Higher the use of descriptive analytics; greater is the use of training for skill-gap in select banks	DA → TSG (+)
H15	Higher the use of prescriptive analytics; greater is the use of post training analytics in select banks	Pres_A → PTA (+)
H16	Higher the use of prescriptive analytics; greater is the use of financial analytics of training in select banks	Pres_A → FAT (+)
H17	Higher the use of prescriptive analytics; greater is the use of training for skill-gap in select banks	Pres_A → TSG (+)
H18	Higher the use of predictive analytics; greater is the use of post training analytics in select banks	Pred_A → PTA (+)
H19	Higher the use of predictive analytics; greater is the use of financial analytics of training in select banks	Pred_A → FAT (+)
H20	Higher the use of predictive analytics; greater is the use of training for skill-gap in select banks	Pred_A → TSG (+)
Note: DA: descriptive analytics; Pres_A: prescriptive analytics; Pred_A: predictive analytics; PTA: post training analytics; FAT: financial analytics of training; TSG: training for skill-gap		
Source: Authors' Calculation		

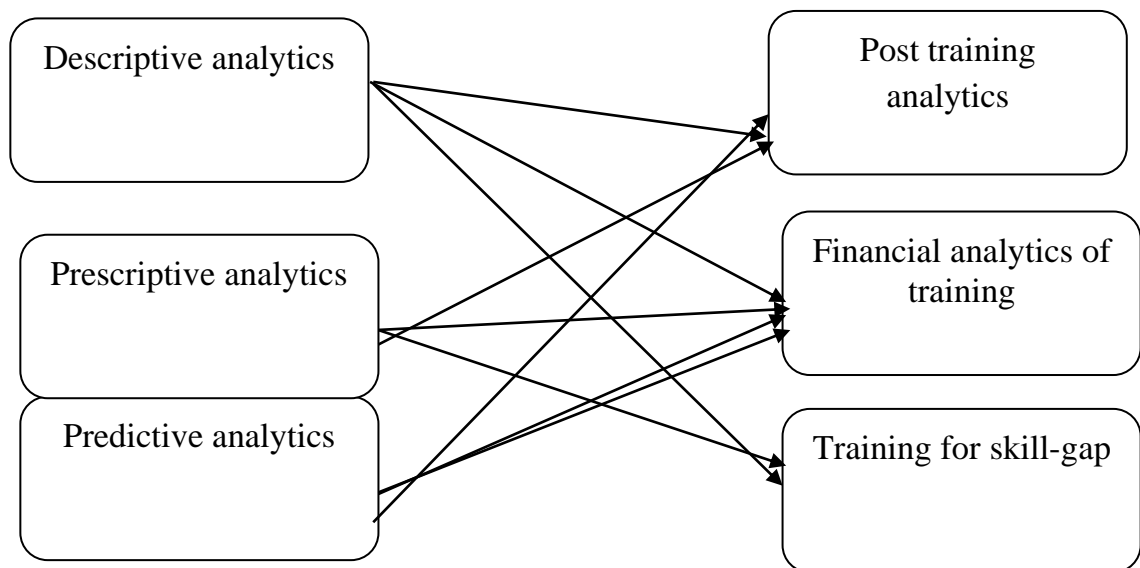


Figure 4.11: The conceptual model for examining the effect of various types of HR analytics on training and development in select banks

It consists of three exogenous variables ‘Descriptive analytics’, ‘Predictive analytics’ and ‘Prescriptive analytics’ and three endogenous variables as ‘post training analytics’, ‘financial analytics of training’ and ‘training for skill-gap identification’. The path diagram shows dependence post training analytics, financial analytics of training and training for skill-gap identification on descriptive analytics, predictive analytics, and prescriptive analytics. Hypothesized relationships are presented through path diagrams in structural equation modeling. The figure 4.10 shows the relationship between HR analytics and training and development.

In Table 4.32 above, the ‘+’ sign shows a positive linear relationship among variables. Based on these hypotheses, the current study established a conceptual model, shown in the accompanying figure. The measurement model was also subjected to Confirmatory Factor Analysis (CFA), and the model’s validity and reliability were investigated.

4.5.2.3 Testing measurement model ‘the effect of various types of HR analytics on training and development in banks’

The measurement model was tested for both reliability and validity. The statistics about reliability and validity were obtained using confirmatory factor analysis (CFA) in AMOS. The information in this regard is given as under:

4.5.2.4 Reliability of the constructs

A construct is said to be reliable if it generates similar results over time, given that measurement conditions remain the same. The constructs’ reliability in the model was tested with the help of ‘composite reliability’, denoted by CR in the table below.

Composite reliability (CR) for each construct was found to be greater than 0.70, a minimum cut-off value for constructs to be reliable (Nunnally, 1978). Therefore, it is concluded that the constructs used in the measurement model were reliable.

4.5.2.5 Validity of the constructs

The validity of a construct refers the degree to which a construct measures what it is supposed to measure. The present study tested two types of validity: convergent and discriminant. First, convergent validity refers to the degree to which two or more measures are related in a construct. The findings revealed that the average variance extracted (AVE) for each construct was more significant than 0.5, the minimum cut-off value for a construct to have convergent validity (Fornell & Larcker, 1981).

Table 4.33 Statistics showing the reliability and validity of the model

	CR	AVE	FAT	DA	Pred_A	Pres_A	PTA	TSG
FAT	0.918	0.695	0.833					
DA	0.881	0.600	0.025	0.775				
Pred_A	0.845	0.522	-0.034	0.514	0.723			
Pres_A	0.831	0.571	-0.083	0.390	0.378	0.756		
PTA	0.912	0.644	0.195	-0.043	-0.010	0.006	0.802	
TSG	0.758	0.516	0.426	0.051	0.050	-0.048	-0.126	0.718

Note: DA: descriptive analytics; Pres_A: prescriptive analytics; Pred_A: predictive analytics; PTA: post training analytics; FAT: financial analytics of training; TSG: training for skill-gap; CR represent composite reliability; and AVE represent Average variance extracted

Source: Authors' Calculation

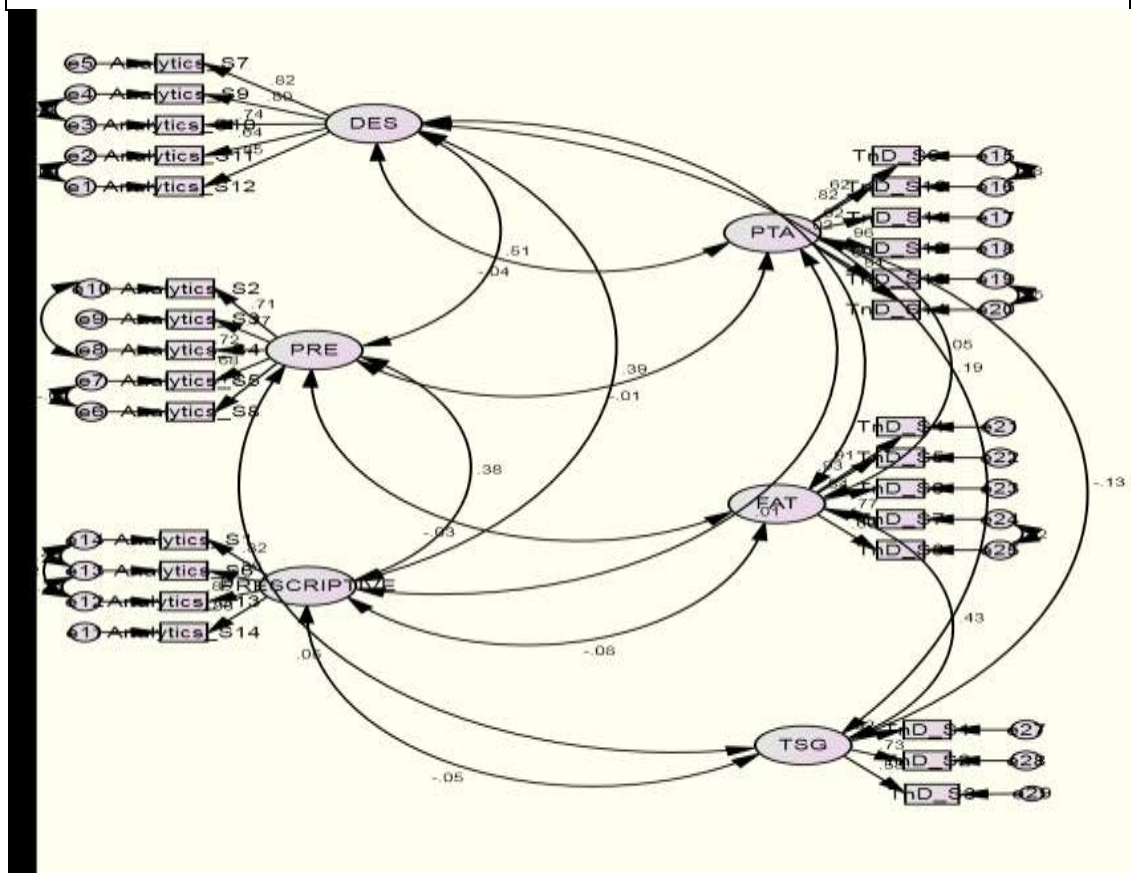


Figure 4.12: The path diagram for the hypothesized relationship of descriptive analytics, predictive analytics and prescriptive analytics and post-training analytics, financial analytics of training, and training for skill gap

For example, in Table 4.33, diagonal values are the square root of AVE, and off-diagonal values represent values of pairwise correlations among respective constructs. The correlations between constructs (off-diagonal values) were found to be less than the square root of AVE (diagonal values). These findings supported the discriminant validity of the constructs used in the model. Further, results indicate an acceptable fit of the measurement model as various statistics supported the fit of the measurement model, as given in table 4.34. Findings highlighted that the statistics given in the above table meet the specified criteria given by different authors. Therefore, the present measurement model is an adequately fit.

Table 4.34 Fit indices of the measurement model ‘the effect of various types of HR analytics on training and development in banks’

Sr. No.	Indices with value	Recommended value	Reference
1	Chi-square=712.59, $p < 0.001$; dof=325; chi-square/dof=2.193	chi-square/dof < 3	Hair et al., 2006
2	Goodness of fit (GFI) = 0.888	GFI > 0.8	Baumgartner & Homburg, 1996
3	Comparative Fit Index (CFI) = 0.946	CFI > 0.9	Hair et al. 2006
4	Tucker-Lewis Index (TLI) = 0.937	TLI > 0.9	Hair et al. 2006
5	Root Mean Square Error of Approximation (RMSEA) = 0.055	RMSEA < 0.08	Steiger, 1990
Note: dof: degrees of freedom			

4.5.2.6 Testing structural model ‘the effect of various types of HR analytics on training and development in banks’

The present study proposed nine hypotheses to examine the effect of various types of HR analytics on training and development in banks. These hypotheses were empirically tested with the help of SEM. Findings in this regard are mentioned in the following table 4.35. The results of the model are used to examine the hypothesized relationship between variables: Descriptive analytics and post-training analytics; descriptive analytics and financial analytics of training; descriptive analytics and training for skill gap; predictive analytics and post-training analytics; predictive

analytics and training for skill gap; predictive analytics and financial analytics of training; prescriptive analytics and post-training analytics; prescriptive analytics and financial analytics of activity; prescriptive analytics and training for skill gap.

Table 4.35: Results of the structural model: ‘the effect of various types of HR analytics on training and development in banks’

Sr. No.	Proposed hypotheses	Relationship	Estimate (β)	t value	p value
H12	Higher the use of descriptive analytics; greater is the use of post training analytics in select banks	DA \rightarrow PTA (+)	0.223	3.892	0.000*
H13	Higher the use of descriptive analytics; greater is the use of financial analytics of training in select banks	DA \rightarrow FAT (+)	0.389	6.385	0.000*
H14	Higher the use of descriptive analytics; greater is the use of training for skill-gap in select banks	DA \rightarrow TSG (+)	0.032	0.649	0.516
H15	Higher the use of prescriptive analytics; greater is the use of post training analytics in select banks	Pres_A \rightarrow PTA (+)	0.137	2.472	0.013*
H16	Higher the use of prescriptive analytics; greater is the use of financial analytics of training in select banks	Pres_A \rightarrow FAT (+)	0.182	3.236	0.001*
H17	Higher the use of prescriptive analytics; greater is the use of training for skill-gap in select banks	Pres_A \rightarrow TSG (+)	1.011	10.011	0.000*
H18	Higher the use of predictive analytics; greater is the use of post training analytics in select banks	Pred_A \rightarrow PTA (+)	0.163	3.178	0.001*
H19	Higher the use of predictive analytics; greater is the use of financial analytics of training in select banks	Pred_A \rightarrow FAT (+)	-0.012	-0.242	0.809
H20	Higher the use of predictive analytics; greater is the use of training for skill-gap in select banks	Pred_A \rightarrow TSG (+)	-0.014	-0.598	0.550
* Significant at 5 percent level of significance.					
Notes: DA: descriptive analytics; Pres_A: prescriptive analytics; Pred_A: predictive analytics; PTA: post training analytics; FAT: financial analytics of training; TSG: training for skill-gap.					

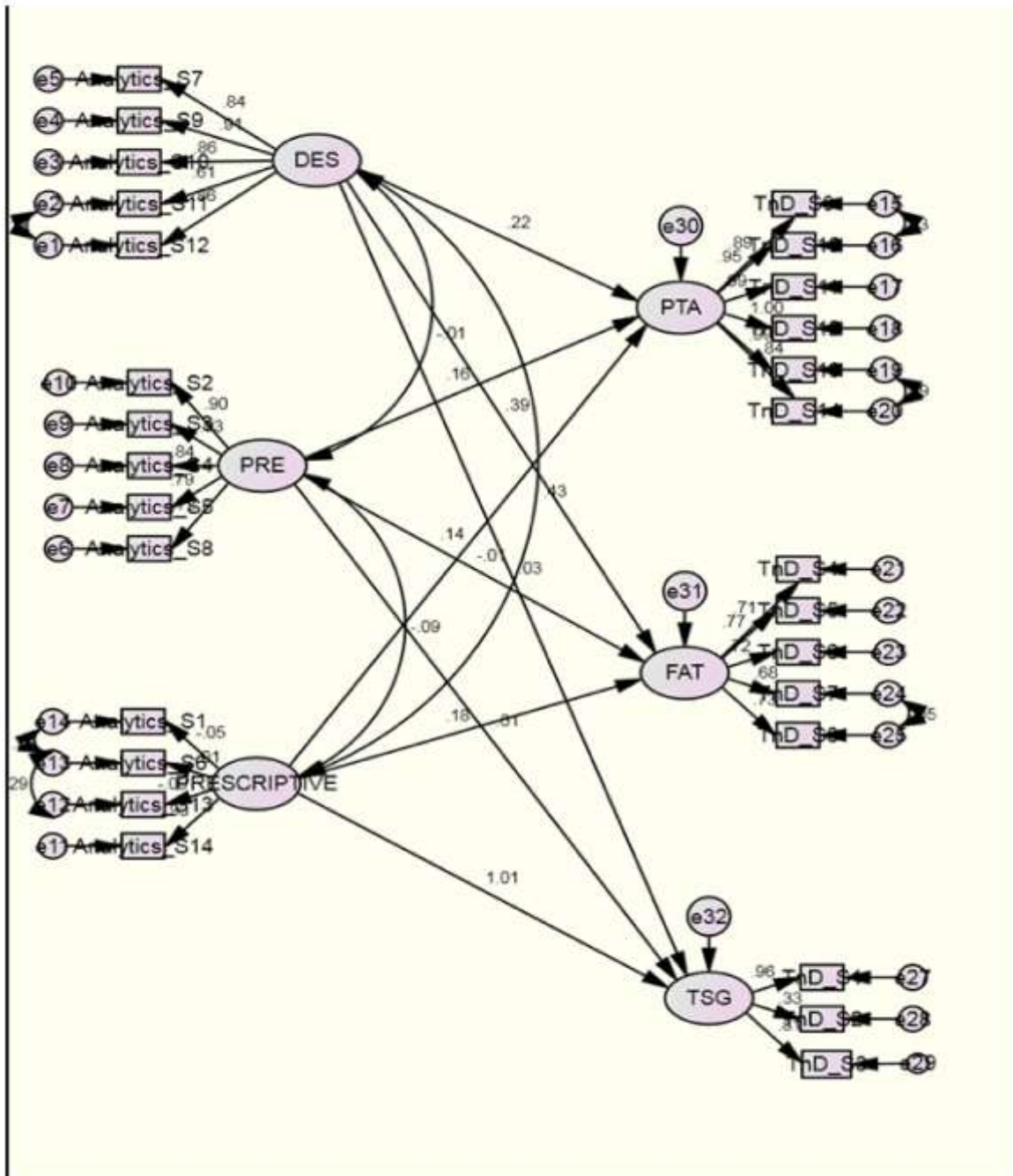


Figure 4.13: The path diagram for the hypothesized relationship of descriptive analytics, predictive analytics and prescriptive analytics and post-training analytics, financial analytics of training, and training for skill gap

The results of the model are used to examine the hypothesized relationship between variables: Descriptive analytics and post-training analytics; descriptive analytics and

financial analytics of training; descriptive analytics and training for skill gap; predictive analytics and post-training analytics; predictive analytics and training for skill gap; predictive analytics and financial analytics of training; prescriptive analytics and post-training analytics; prescriptive analytics and financial analytics of activity; prescriptive analytics and training for skill gap.

H12: Higher, the use of descriptive analytics, the greater, is the use of post-training analytics in select banks

The connecting path between descriptive analytics and post-training analytics yields Beta value= 0.223, Critical ratio=3.892, which is statistically significant as P-value <0.05 which means higher the use of descriptive analytics, the greater is the use of post-training analytics in select banks. Thus, H12 is accepted

H13: Higher the use of descriptive analytics, greater is the use of financial analytics of training in select banks

The connecting path between descriptive analytics and financial analytics of training yields Beta value= 0.389, a Critical ratio=6.385, which is statistically significant as P-value <0.05 which means higher the use of descriptive analytics; greater is the use of financial analytics of training in select banks. Thus, H13 is accepted

H14: Higher the use of descriptive analytics; greater is the use of training for skill-gap in select banks

The connecting path between descriptive analytics and training for skill-gap yields Beta value= 0.032, Critical ratio=0.649, which is statistically not significant as P-value >0.05, which means higher the use of descriptive analytics; lesser is the use of training for skill-gap in select banks

Thus, H14 is not accepted

H15: Higher, the use of prescriptive analytics, the greater, is the use of post-training analytics in select banks

The connecting path between prescriptive analytics and post training analytics yields Beta value= 0.137, Critical ratio=6.385, which is statistically significant as P-value >0.05 which means the Higher the use of prescriptive analytics, the lesser the use of post-training analytics in select banks. Thus, H15 is not accepted

H16: Higher, the use of prescriptive analytics, the greater, is the use of financial analytics of training in select banks

The connecting path between prescriptive analytics and financial analytics of training yields Beta value= 0.182, Critical ratio=3.236, which is statistically significant as P-value <0.05 which means Higher the use of prescriptive analytics; the greater is the use of financial analytics of training in select banks. Thus, H16 is accepted

H17: Higher, the use of prescriptive analytics, the greater, is the use of training for skill-gap in select banks

The connecting path between prescriptive analytics and training for skill gap yields Beta value= 1.011, Critical ratio=10.011, which is statistically significant as P-value <0.05 which means higher the use of prescriptive analytics, the greater is the use of training for skill-gap in select banks. Thus, H17 is accepted

H18: Higher, the use of predictive analytics, the greater, is the use of post-training analytics in select banks

The connecting path between predictive analytics and post-training analytics yields a Beta value= 0.163, Critical ratio=3.178, which is statistically significant as P-value <0.05 which means higher the use of predictive analytics, the greater is the use of post-training analytics in select banks. Thus, H18 is accepted

H19: Higher the use of predictive analytics, greater is the use of financial analytics of training in select banks

The connecting path between predictive analytics and financial analytics of training yields Beta value= 0.032, Critical ratio=0.649, which is statistically not significant as P-value >0.05 which means Higher the use of predictive analytics; lesser is the use of financial analytics of training in select banks. Thus, H19 is not accepted

H20: Higher, the use of predictive analytics, the greater, is the use of training for skill gap in select banks

The connecting path between predictive analytics and training for skill-gap yields Beta value= 0.032, Critical ratio=0.649, which is statistically not significant as P-value >0.05 which means higher the use of predictive analytics; the lesser is the use of training for skill-gap in select banks. Thus, H20 is not accepted.

4.5.3 Factors of performance management in select banks

Before using EFA on 12 statements of performance management in select banks, the study calculated mean score and standard deviation for these statements. Findings regarding mean score and standard deviation for these statements are given in table 4.36.

Findings revealed that respondents agreed with the performance management statements. Respondents agreed that banks determine the average time of employees' promotion in each fiscal year, and organizations also assess total promotions over total transfer rate in each fiscal year.

Table 4.36: Mean score and standard deviation for statements on performance management in select banks

Sr. No.	Statements	Mean score	Standard deviation
1	This organization determines the average time of employees' promotion in each fiscal year	4.69	1.813
2	This organization assess total promotions over total transfer rate in each fiscal year	4.69	1.737
3	This organization prepares competency level skill inventory for each of its branch	4.65	1.736
4	There is a system to track satisfaction of new hires in this organization	4.92	1.605
5	This organization determines percentage of staff working at acceptable performance level in every branch	4.75	1.661
6	This organization measures staff competencies to deliver business goals in every branch	4.76	1.594
7	This organization measures educational level of its staff at each hierarchical level in branch	4.85	1.579
8	This organization determines effectiveness of performance management processes every fiscal year	4.82	1.593
9	This organization measures extent to which performance management are aligned to business goals	4.78	1.571
10	There is a system to measure percentage of personnel development plans complying with business plans each yea	4.63	1.589
11	There is a system to measure percentage of personnel development plans achieved by functional area every year	4.73	1.660
12	This organization has deployed productivity measures such as revenue per employee	4.53	1.684

It was found that banks prepare competency-level skill inventory for each branch and have a system to track the satisfaction of new hires in banks. Banks were found to determine the percentage of staff working at acceptable performance levels in every branch and to measure staff competencies to deliver business goals in every department. Findings suggested that banks measure the educational level of their staff at each hierarchical level in the branch and determine the effectiveness of performance management processes every fiscal year.

4.5.3.1 Performance management analytics for public and private sector banks

Examining the intensity of using various HR analytics in public and private sector banks is essential.

Table 4.37: Performance management analytics for public and private sector banks

Performance management analytics	Mean	
	Public sector banks	Private sector banks
This organization determines the average time of employees' promotion in each fiscal year	4.15	5.25
This organization assess total promotions over total transfer rate in each fiscal year	4.20	5.19
This organization prepares competency level skill inventory for each of its branch	4.23	5.07
There is a system to track satisfaction of new hires in this organization	4.69	5.15
This organization determines percentage of staff working at acceptable performance level in every branch	4.69	4.82
This organization measures staff competencies to deliver business goals in every branch	4.65	4.87
This organization measures educational level of its staff at each hierarchical level in branch	4.66	5.03
This organization determines effectiveness of performance management processes every fiscal year	4.70	4.95
This organization measures extent to which performance management are aligned to business goals	4.56	5.01
There is a system to measure percentage of personnel development plans complying with business plans each yea	4.20	5.07

There is a system to measure percentage of personnel development plans achieved by functional area every year	4.44	5.03
This organization has deployed productivity measures such as revenue per employee	4.18	4.88
Source: Authors' Calculation		

Therefore, the present study compared performance management analytics for public and private sector banks. For this, the mean score for all statements under performance management analytics was compared for both public and private sector banks. Findings regarding comparing the use of performance management analytics for public and private sector banks are given in table 4.37

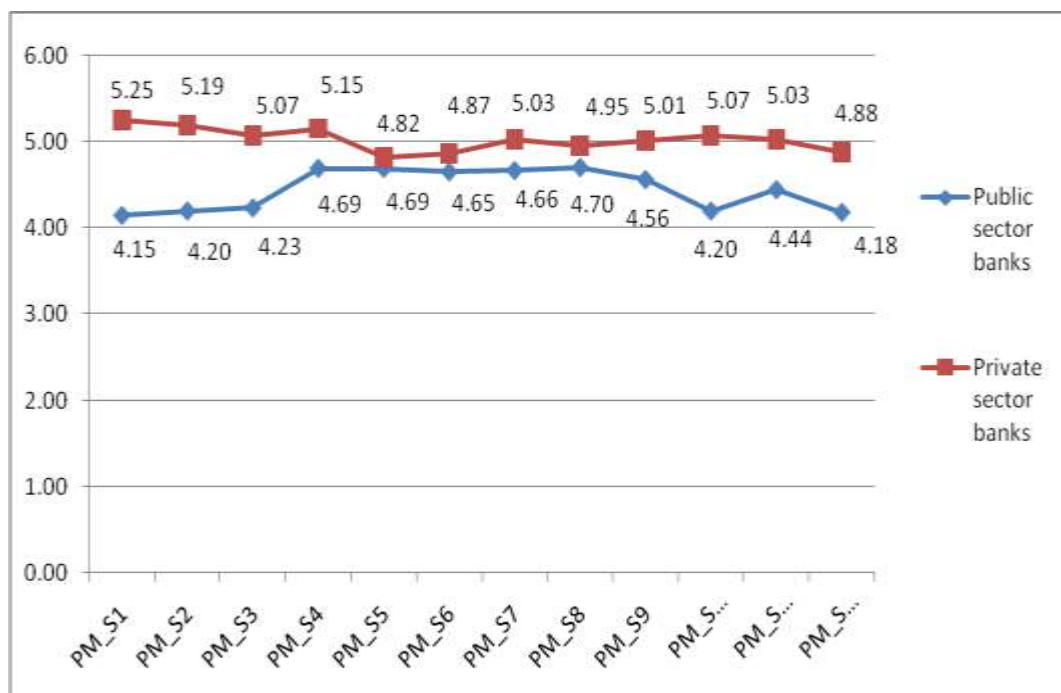


Figure 4.14: Performance Management in Public and Private Banks

It is evident from the above-mentioned findings that private sector banks have outperformed public sector banks in terms of using performance management analytics. The mean score for all statements under performance management analytics for private banks was found to be higher than the mean score of public sector banks.

Further, the study used KMO and Bartlett's Test of Sphericity before applying EFA on 12 statements of performance management in select banks. First, sampling adequacy was examined using KMO test. This test suggests that the value of KMO

varies from 0 to 1; a higher value of KMO (close to 1.0) implies that applying EFA on the given data is useful. Second, Bartlett's Test of Sphericity was used to examine the presence of correlation among variables.

Table 4.38: “Findings of KMO and Bartlett's Test”

“Kaiser-Meyer-Olkin Measure of Sampling Adequacy”		.714
“Bartlett's Test of Sphericity”	“Approx. Chi-Square”	2343.6
	Degree of freedom	66
	“Sig. (p)”	.000
Source: Authors’ Calculation		

This test diagnoses the relatedness of the variables considered in the study and further throws light on detecting the factor structure. Findings of KMO and Bartlett's Test are given in the table above. Findings of “KMO and Bartlett's Test” (refer to the table given above) highlighted that value of KMO 0.714, which is greater than the recommended value of 0.7 (Hair *et al* 2006). Therefore, it was concluded that the sample used in the study is adequate, which justifies using EFA on given data. Moreover, chi-square value for Bartlett's Test of Sphericity was found to be 2343.6 and p value was less than 0.05 (level of significance). This finding indicated the presence of significant correlation among statements relating to bank performance management. Therefore, the KMO and Bartlett's Test findings were helpful in concluding that the application of EFA on given data is justified. Figure 4.14 represents Performance Management Scree plot. Findings of EFA on 12 statements of performance management banks produced three factors as given below:

- Factor 1: Skill competency analytics
- Factor 2: Promotion of competency analytics
- Factor 3: Satisfaction and productivity analytics

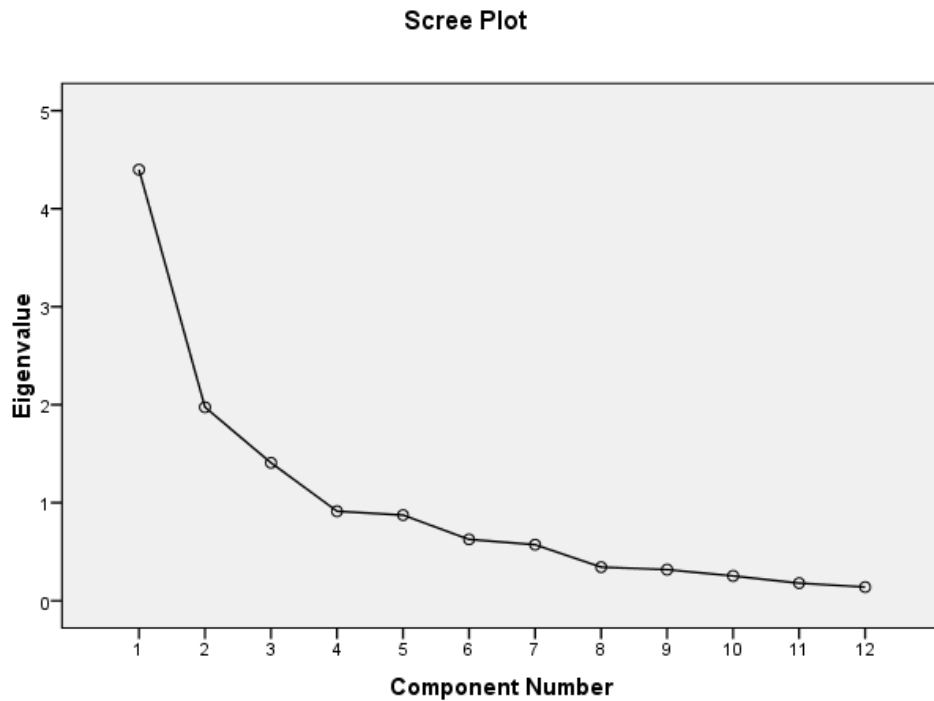


Figure 4.15: Scree plot of Performance Management

The first factor was named ‘skill competency analytics’, which included five statements. This factor was found to be the significant factor in terms of explaining variance in the data. For instance, the first factor was able to explain 26.26% variance in the data. It was observed that respondents have positive perceptions of skill competency analytics being used in their organizations. Respondents believed that banks have been using HR analytics to measure staff competencies to deliver business goals in every branch and to measure its staff’s educational level at each branch’s hierarchical level. Banks were found to use HR analytics to measure the effectiveness of performance management processes every fiscal year and to know how well performance management aligns with business goals. The following table 4.39 includes factor loadings of statements that were loaded on ‘skill competency analytics’:

Table 4.39: Factor loadings of statements under ‘skill competency analytics’

Statements	Factor loadings
This organization measures the extent to which performance management are aligned to business goals	.856
This organization determines the effectiveness of performance management processes every fiscal year	.812
This organization measures the educational level of its staff at each hierarchical level in the branch	.781
This organization measures staff competencies to deliver business goals in every branch	.646
There is a system to measure the percentage of personnel development plans achieved by the functional area every year	.482
Variance explained	26.26%
Reliability of the scale (Cronbach alpha)	.798
Source: Authors’ calculation	

Findings of Exploratory Factor Analysis (EFA) on 12 statements on performance management in select banks produced three factors, and the second factor was named ‘promotion competency analytics’, which included four statements. This factor was found to be the second most significant factor in terms of explaining variance in the data. For instance, the first factor was able to explain a 21.46% variance in the data

Table 4.40 Factor loadings of statements under ‘promotion competency analytics’

Statements	Factor loadings
This organization assess total promotions over total transfer rate in each fiscal year	.897
This organization prepares competency level skill inventory for each of its branch	.867
This organization determines the average time of employees' promotion in each fiscal year	.836
This organization determines percentage of staff working at acceptable performance level in every branch	.466
Variance explained	21.46%
Reliability of the scale (Cronbach alpha)	.824
Source: Authors’ Calculation	

In addition, findings highlighted that banks have been using HR analytics to determine the average time of employees' promotion to assess total promotions over total transfer rate in each fiscal year and to prepare competency level skill inventory for each of its branch. The following table 4.40 includes factor loadings of statements that were loaded onto 'promotion competency analytics'.

Findings of EFA on 12 statements on performance management in select banks produced three factors and the third factor was named 'satisfaction and productivity analytics', which included three statements. This factor was found to be the third most significant factor in terms of explaining variance in the data. For instance, the first factor was able to explain a 17.11% variance in the data. It was found that using analytics in banks helps to measure percentage of personnel development plans complying with business plans each year; to measure productivity measures such as revenue per employee; and to track satisfaction of new hires in this organization. The following table includes factor loadings of statements that were loaded onto third factor 'satisfaction and productivity analytics':

Table 4.41 Factor loadings of statements under 'satisfaction and productivity analytics'

Statements	Factor loadings
There is a system to track satisfaction of new hires in this organization	.895
There is a system to measure percentage of personnel development plans complying with business plans each year	.744
This organization has deployed productivity measures such as revenue per employee	.632
Variance explained	17.11%
Reliability of the scale (Cronbach alpha)	.719
Source: Authors' Calculation	

4.5.3.2 Effect of various types of HR analytics on performance management

Structural Equation Modeling through AMOS has been used to analyze the effects of Descriptive analytics, Predictive analytics, and Prescriptive analytics on skill competency analytics, promotion competency analytics, and satisfaction and productivity analysis. Hypothesized relationships are presented through path diagrams

in structural equation modeling. The figure 4.15 shows the relationship between HR analytics and performance management. It consists of three exogenous variables, ‘Descriptive analytics’, ‘Predictive analytics’, and ‘Prescriptive analytics’, and three endogenous variables, ‘skill competency analytics’, ‘promotion competency analytics’, and ‘satisfaction and productivity analytics’ as endogenous variables. The path diagram shows the dependence of skill competency analytics, promotion competency analytics, and satisfaction and productivity analytics on predictive analytics and prescriptive analytics.

Table 4.42: Identification of Factors

Types of HR analytics	Factors of performance management
Descriptive analytics	Skill competency analytics
Prescriptive analytics	Promotion competency analytics
Predictive analytics	Satisfaction and productivity analytics

Structural Equation Modeling (SEM) was run among three factors of HR analytics and three factors of performance management. On the basis of the pertinent literature, the study proposed nine relationships between factors of HR analytics and performance management in banks as mentioned in the table 4.43. The ‘+’ sign in the above table shows a positive linear relationship among variables. Based on these hypotheses, the current study established a conceptual model, shown in the accompanying figure. Moreover, confirmatory factor analysis (CFA) was applied on the measurement model; wherein reliability and validity of the model were also examined.

Table 4.43: Hypotheses proposed to examine the effect of various types of HR analytics on performance management in banks

Sr. No.	Proposed hypotheses	Relationship
H21	The higher the use of descriptive analytics, the greater the use of skill competency analytics in select banks	DA → SCA (+)
H22	The higher the use of descriptive analytics, the greater the use of promotion competency analytics in select banks	DA → PCA (+)
H23	The higher the use of descriptive analytics, the greater the use of satisfaction and productivity analytics in select banks	DA → SPA (+)
H24	The higher the use of prescriptive analytics, the greater is the use of skill competency analytics in select banks	Pres_A → SCA (+)
H25	The higher the use of prescriptive analytics, the greater is the use of promotion competency analytics in select banks	Pres_A → PCA (+)
H26	The higher the use of prescriptive analytics, the greater is the use of satisfaction and productivity analytics in select banks	Pres_A → SPA (+)
H27	The higher the use of predictive analytics; the greater is the use of skill competency analytics in select banks	Pred_A → SCA (+)
H28	The higher the use of predictive analytics, greater is the use of promotion competency analytics in select banks	Pred_A → PCA (+)
H29	The higher the use of predictive analytics; the greater is the use of satisfaction and productivity analytics in select banks	Pred_A → SPA (+)

Note: DA: descriptive analytics; Pres_A: prescriptive analytics; Pred_A: predictive analytics; SCA: skill competency analytics; PCA: promotion competency analytics; SPA: satisfaction and productivity analytics

Source: Authors' Calculation

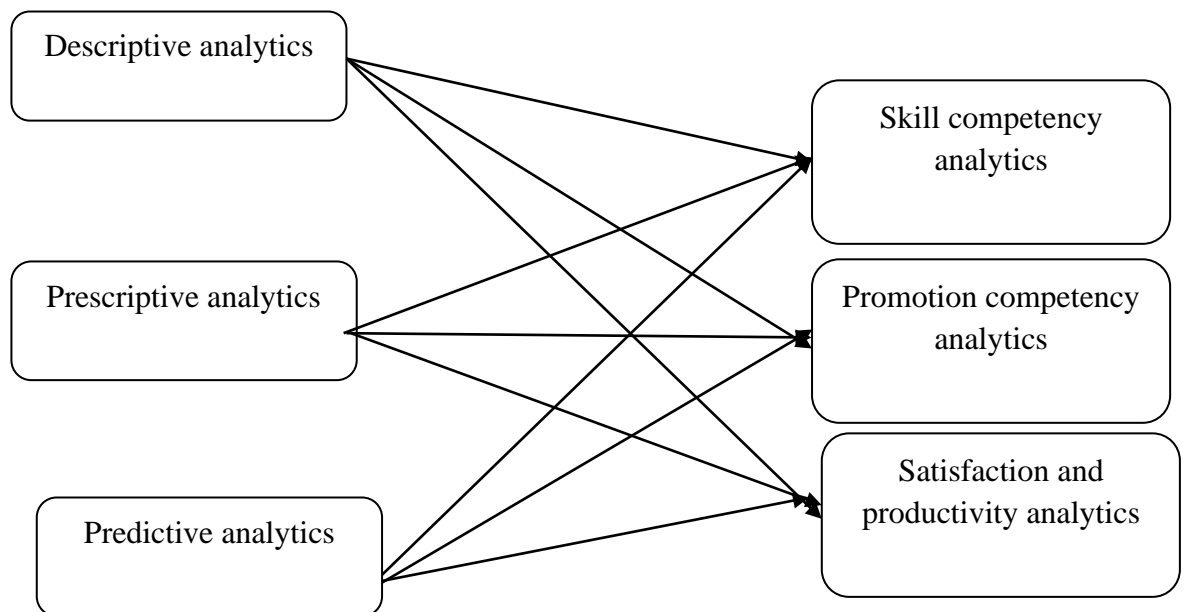


Figure 4.16: The conceptual model for examining the effect of various types of HR analytics on performance management in select banks

4.5.3.3 Testing measurement model ‘the effect of various types of HR analytics on performance management in banks’

The measurement model was tested for both reliability and validity. The statistics pertaining to reliability and validity were obtained using confirmatory factor analysis (CFA) in AMOS. The information in this regard is given as under:

4.5.3.4 Reliability of the constructs

A construct is said to be reliable if it generates similar results over time, given that conditions of measurement remain the same. The reliability of the constructs included in the model was tested with the help of ‘composite reliability’, denoted by CR in the table below. Composite reliability (CR) for each construct was more significant than 0.70, a minimum cut-off value for constructs to be reliable (Nunnally, 1978). Therefore, it is concluded that the constructs used in the measurement model were reliable.

4.5.3.5 Validity of the constructs

The validity of a construct refers to the degree to which a construct measures what it is supposed to measure. The present study tested two types of validity: convergent validity and discriminant validity. First, convergent validity refers to the degree to which two or more measures used in a construct are related to each other. The findings revealed that the average variance extracted (AVE) for each construct was more significant than 0.5, the minimum cut-off value for a construct to have convergent validity (Fornell & Larcker, 1981). These findings established the convergent validity of the constructs used in the study. Second, discriminant validity conceptualizes that constructs used in a study differ significantly from each other. In the following table 4.46 diagonal values are the square root of AVE and off-diagonal values represent values of pair wise correlations among respective constructs. The correlations between constructs (off-diagonal values) were found to be less than the square root of AVE (diagonal values). These findings supported the discriminant validity of the constructs used in the model. Moreover, every item under a specific construct was found to have factor loading greater than 0.5 (Fornell & Larcker, 1981). This finding reveals that there is convergent validity among the scales used.

Table 4.44: Statistics showing reliability and validity of the model

	CR	AVE	PCA	DA	Pred_A	Pres_A	SCA	SPA
PCA	0.811	0.543	0.737					
DA	0.881	0.599	-0.148	0.774				
Pred_A	0.845	0.522	-0.133	0.514	0.722			
Pres_A	0.868	0.629	-0.013	0.369	0.391	0.793		
SCA	0.919	0.694	0.254	-0.113	-0.109	-0.028	0.833	
SPA	0.854	0.672	0.069	-0.038	-0.034	-0.040	0.307	0.820

Note: DA: descriptive analytics; Pres_A: prescriptive analytics; Pred_A: predictive analytics; SCA: skill competency analytics; PCA: promotion competency analytics; SPA: satisfaction and productivity analytics; CR represent composite reliability; and AVE represent Average variance extracted

Table 4.45: Fit indices of the measurement model ‘the effect of various types of HR analytics on performance management in banks’

Sr. No.	Indices with value	Recommended value	Reference
1	Chi-square=625.501, p<0.001; dof=279; chi-square/dof=2.242	chi-square/dof< 3	Hair et al., 2006
2	Goodness of fit (GFI) = 0.868	GFI > 0.8	Baumgartner & Homburg, 1996
3	Comparative Fit Index (CFI) = 0.943	CFI > 0.9	Hair et al. 2006
4	Tucker-Lewis Index (TLI) = 0.934	TLI > 0.9	Hair et al. 2006
5	Root Mean Square Error of Approximation (RMSEA) = 0.056	RMSEA < 0.08	Steiger, 1990

Note: dof: degrees of freedom

Source: Authors’ Calculation

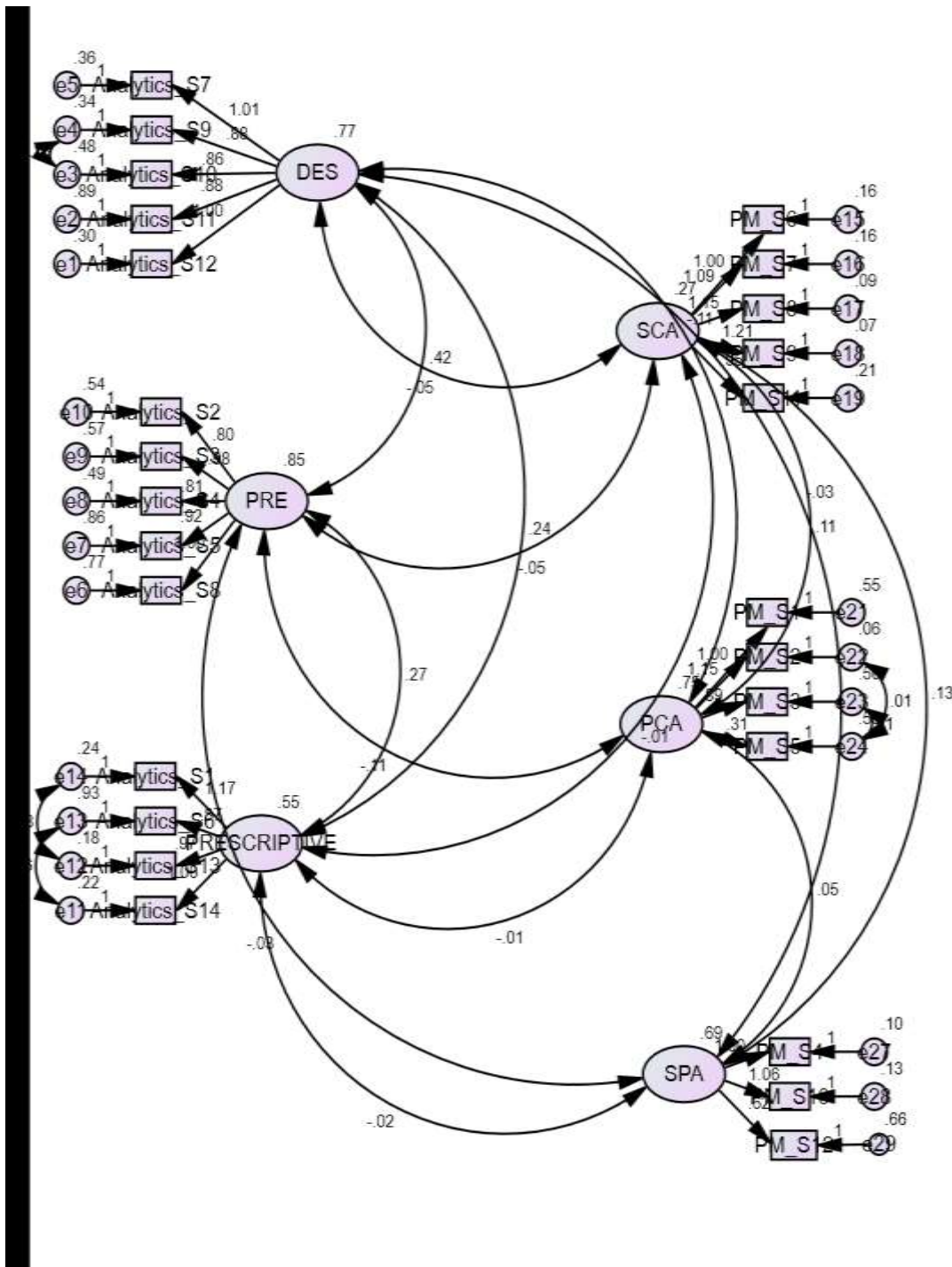


Figure 4.17 The path diagram for the hypothesized relationship of descriptive analytics, predictive analytics and prescriptive analytics and skill competency analytics, promotion competency analytics and satisfaction and productivity analytics

Further, results indicate an acceptable fit of the measurement model as various statistics supported the fit of the measurement model, as given in the following table.

Table 4.46: Results of the structural model: ‘the effect of various types of HR analytics on performance management in banks’

Sr. No.	Proposed hypotheses	Relationship	Estimate (β)	t value	p value
H21	The higher the use of descriptive analytics, the greater the use of skill competency analytics in select banks	DA→SCA (+)	0.244	4.247	0.000*
H22	The higher the use of descriptive analytics, the greater the use of promotion competency analytics in select banks	DA→PCA (+)	0.442	7.218	0.000*
H23	The higher the use of descriptive analytics, the greater the use of satisfaction and productivity analytics in select banks	DA→SPA (+)	0.028	0.543	0.587
H24	The higher the use of prescriptive analytics, the greater the use of skill competency analytics in select banks	Pres_A→SCA (+)	0.159	2.871	0.004*
H25	The higher the use of prescriptive analytics, the greater the use of promotion competency analytics in select banks	Pres_A→PCA (+)	0.144	2.548	0.011*
H26	The higher the use of prescriptive analytics, the greater the use of satisfaction and productivity analytics in select banks	Pres_A→SPA (+)	1.015	5.575	0.000*
H27	The higher the use of predictive analytics, the greater the use of skill competency analytics in select banks	Pred_A→SCA (+)	0.145	2.837	0.005*
H28	The higher the use of predictive analytics, the greater the use of promotion competency analytics in select banks	Pred_A→PCA (+)	0.004	0.070	0.945
H29	The higher the use of predictive analytics, the greater the use of satisfaction and productivity analytics in select banks	Pred_A→SPA (+)	-0.013	-0.557	0.578
<p>* Significant at 5 percent level of significance. Notes: DA: descriptive analytics; Pres_A: prescriptive analytics; Pred_A: predictive analytics; SCA: skill competency analytics; PCA: promotion competency analytics; SPA: satisfaction and productivity analytics.</p>					
Source: Authors' Calculation					

Findings highlighted that the statistics given in the above table meet the specified criteria given by different authors. Therefore, the present measurement model is adequately fit.

4.5.3.6 Testing structural model ‘the effect of various types of HR analytics on performance management in banks’

The present study proposed nine hypotheses to examine the impact of multiple HR analytics types on banks' training and development. These hypotheses were empirically tested with the help of SEM. The results of the model are used to examine the hypothesized relationship between variables: Descriptive analytics and skill competency analytics; descriptive analytics and promotion competency analytics; descriptive analytics and satisfaction and productivity analytics; predictive analytics and skill competency analytics; predictive analytics and promotion competency analytics; predictive analytics and satisfaction and productivity analytics; prescriptive analytics and skill competency analytics; prescriptive analytics and promotion competency analytics; prescriptive analytics and satisfaction and productivity analytics.

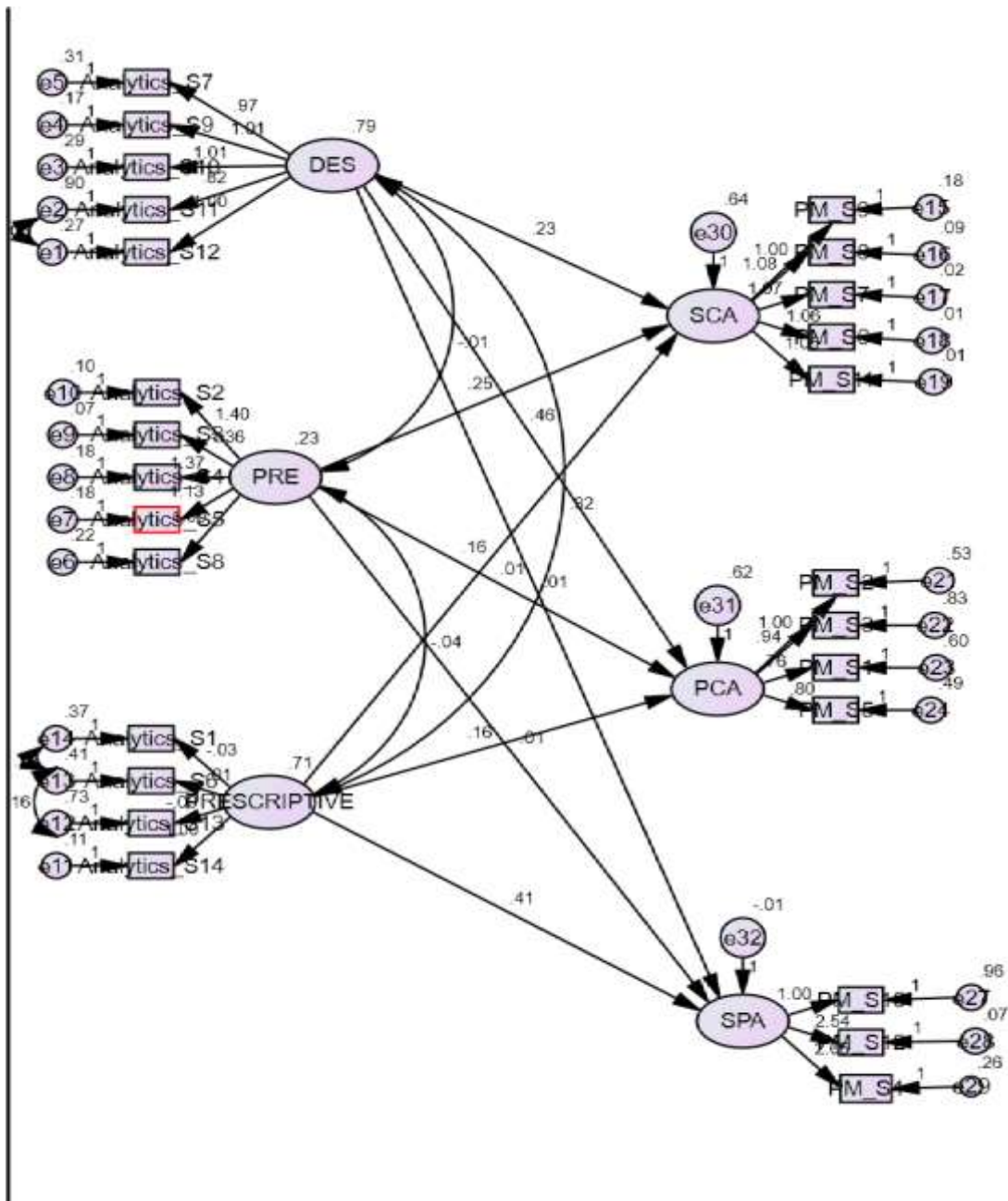


Figure 4.18: The path diagram for the hypothesized relationship of descriptive analytics, predictive analytics and prescriptive analytics and skill competency analytics, promotion competency analytics and satisfaction and productivity analytics

H21: Higher the use of descriptive analytics; greater is the use of skill competency analytics in select banks.

The connecting path between descriptive analytics and skill competency analytics yields Beta value= 0.244, Critical ratio=4.247, which is statistically significant as P-value <0.05 which means higher the use of descriptive analytics; greater is the use of skill competency analytics in select banks. Thus, H21 is accepted

H22: Higher the use of descriptive analytics; greater is the use of promotion competency analytics in select banks

The connecting path between descriptive analytics and promotion competency analytics database yields Beta value= 0.442, Critical ratio= 7.218, which is statistically significant as P-value <0.05 which means higher the use of descriptive analytics; greater is the use of promotion competency analytics in select banks. Thus, H22 is accepted

H23: Higher the use of descriptive analytics; greater is the use of satisfaction and productivity analytics in select banks

The connecting path between descriptive analytics and satisfaction and productivity analytics database yields Beta value= 0.028, Critical ratio= 0.543, which is statistically significant as P-value >0.05 which means higher the use of descriptive analytics; lesser is the use of satisfaction and productivity analytics in select banks. Thus, H23 is not accepted.

H24: Higher the use of prescriptive analytics; greater is the use of skill competency analytics in select banks

The connecting path between prescriptive analytics and skill competency analytics database yields Beta value= 0.159, Critical ratio= 2.871, which is statistically significant as P-value < 0.05 which means higher the use of prescriptive analytics; greater is the use of skill competency analytics in select banks. Thus, H24 is accepted.

H25: Higher the use of prescriptive analytics; greater is the use of promotion competency analytics in select banks

The connecting path between prescriptive analytics and promotion competency analytics database yields Beta value= 0.144, Critical ratio= 2.548, which is

statistically significant as $P\text{-value} > 0.05$ which means higher the use of prescriptive analytics; lesser is the use of promotion competency analytics in select banks. Thus, H25 is accepted.

H26: Higher the use of prescriptive analytics; greater is the use of satisfaction and productivity analytics in select banks

The connecting path between prescriptive analytics and satisfaction and productivity analytics database yields Beta value= 1.015, Critical ratio= 5.575, which is statistically significant as $P\text{-value} < 0.05$ which means higher the use of prescriptive analytics; greater is the use of satisfaction and productivity analytics in select banks. Thus, H26 is accepted.

H27: Higher the use of predictive analytics; greater is the use of skill competency analytics in select banks

The connecting path between predictive analytics and skill competency analytics database yields Beta value= 0.145, Critical ratio= 2.837, which is statistically significant as $P\text{-value} = 0.05$ which means higher the use of predictive analytics; greater is the use of skill competency analytics in select banks. Thus, H27 is accepted.

H28: Higher the use of predictive analytics; greater is the use of promotion competency analytics in select banks

The connecting path between predictive analytics and promotion competency analytics database yields Beta value= 0.004, Critical ratio= 0.070, which is statistically significant as $P\text{-value} > 0.05$ which means higher the use of predictive analytics; greater is the use of greater is the use of promotion competency analytics in select banks. Thus, H28 is not accepted.

H29: Higher the use of predictive analytics; greater is the use of satisfaction and productivity analytics in select banks

The connecting path between predictive analytics and use of satisfaction and productivity analytics Beta value= 0.013, Critical ratio= 0.557, which is statistically significant as $P\text{-value} > 0.05$ which means higher the use of predictive analytics;

greater is the use of greater is the use of satisfaction and productivity analytics in select banks. Thus, H29 is not accepted.

4.5.4 Factors of employee attrition in select banks

Before using EFA on 12 statements of employee attrition in select banks, the study calculated mean score and standard deviation for these statements. Findings regarding the mean score and standard deviation for these statements are given in the following table 4.47.

Table 4.47: Mean score and standard deviation for statements on employee attrition in select banks

Sr. No.	Statements	Mean score	Standard deviation
1	This organization determines staff turnover compared with the market benchmark in every fiscal year	4.64	1.636
2	There is a system to track the employee turnover of best performers in every fiscal year	4.63	1.636
3	This organization keeps track of the average length of service for its staff	4.70	1.670
4	This organization determines the average length of service by region	4.77	1.690
5	This organization determines the average length of service by function	4.79	1.660
6	The average years of experience is determined for each branch in this organization	4.89	1.691
7	There is a system to assess the reasons why employees leave the organization	4.78	1.708
8	This organization measures the annual turnover of employees in key positions in branches	4.66	1.654
9	There is a system to predict the involuntary staff turnover rate in the organization (layoffs and dismissal)	4.65	1.695
10	There is a system to predicting voluntary staff turnover rate in the organization (higher studies, stay-at-home parents, relocation)	4.70	1.680
11	The average retirement rate is determined for each branch	4.68	1.703
12	This organization determines the effectiveness of the process to retain high performers	4.70	1.675
Source: Authors' Calculation			

Findings revealed that respondents agreed with the employee attrition statements. Respondents agreed that banks have developed HR analytics to determine staff turnover compared with a market benchmark in every fiscal year and track employee turnover of best performers in every fiscal year. Managers agreed that HR analytics in banks is in the position to keep track of the average length of service for its staff. It also has a feature to determine average length of service both by region and function of the employee. The average years of experience can also be examined for each bank branch. HR analytics used in the banks was found to assess why employees leave the organization and how employees' annual turnover can also be determined. It was found that both involuntary (layoffs and dismissal) and voluntary staff turnover rate may be determined using HR analytics. HR analytics can also be used to evaluate other crucial factors like the average retirement rate and the success of keeping high-performing workers.

4.5.4.1 Employee attrition analytics for public and private sector banks

Examining the intensity of using various HR analytics in public and private sector banks is essential. Therefore, the present study attempted to compare the difference in the use of employee attrition analytics for public and private sector banks. The mean score for all statements under employee attrition analytics was compared for public and private sector banks. Findings regarding comparing the use of employee attrition analytics for public and private sector banks are given below:

Table 4.48: Employee attrition analytics for public and private sector banks

Employee attrition analytics	Mean	
	Public sector banks	Private sector banks
This organization determines staff turnover compared with the market benchmark in every fiscal year	4.43	4.86
There is a system to track the employee turnover of best performers in every fiscal year	4.39	4.87
This organization keeps track of the average length of service for its staff	4.29	5.10
This organization determines the average length of service by region	4.31	5.22
This organization determines the average length of service by function	4.38	5.21
The average years of experience is determined for each branch in this organization	4.39	5.39
There is a system to assess the reasons why employees leave the organization	4.30	5.27
This organization measures the annual turnover of employees in key positions in branches	4.21	5.11
There is a system to predict the involuntary staff turnover rate in the organization (layoffs and dismissal)	4.24	5.06
There is a system to predicting voluntary staff turnover rate in the organization (higher studies, stay-at-home parents, relocation)	4.30	5.10
The average retirement rate is determined for each branch	4.28	5.08
This organization determines the effectiveness of the process to retain high performers	4.31	5.10
Source: Authors' Calculation		

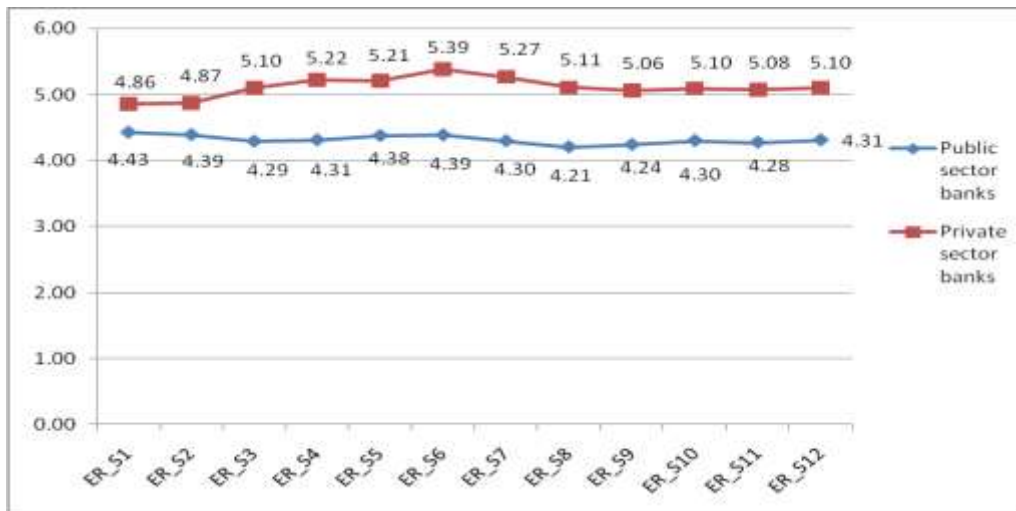


Figure 4.19 Employee retention in Public and Private banks

It is evident from the findings mentioned above that private-sector banks have outperformed public-sector banks in terms of using employee attrition analytics. The mean score for all statements under employee attrition analytics for private banks was found to be higher than the mean score of public sector banks. Further, the study used KMO and Bartlett's Test of Sphericity before applying EFA on 12 statements of employee attrition select banks. First, sampling adequacy was examined using KMO test. This test suggests that the value of KMO varies from 0 to 1; a higher value of KMO (close to 1.0) implies that applying EFA to the given data is valuable. Second, Bartlett's Test of Sphericity was used to examine the correlation among variables. This test diagnoses the relatedness of the variables considered in the study and further throws light on detecting the factor structure. Findings of KMO and Bartlett's Test are given in the table below 4.49:

Table 4.49: “Findings of KMO and Bartlett's Test”

“Kaiser-Meyer-Olkin Measure of Sampling Adequacy”		.796
“Bartlett's Test of Sphericity”	“Approx. Chi-Square”	2970.8
	Degree of freedom	66
	“Sig. (p)”	.000
Source: Authors' Calculation		

Findings of “KMO and Bartlett's Test” (refer to the table given above) highlighted that value of KMO 0.796, which is greater than the recommended value of 0.7 (Hair *et al.*, 2006). Therefore, it was concluded that the sample used in the study is adequate, which justifies the use of EFA on given data. Moreover, the chi-square value for Bartlett's Test of Sphericity was 2970.8, and the p-value was less than 0.05 (level of significance). This finding indicated the presence of a significant correlation among statements relating to bank employee attrition. Therefore, the results of both KMO and Bartlett's Test were useful in concluding that the application of EFA on given data is justified. Findings of EFA on 12 statements of employee attrition in banks produced three factors as given below:

- Factor 1: Retirement analytics
- Factor 2: Service analytics
- Factor 3: Comparative turnover analytics

The first factor was named ‘retirement analytics’, which included five statements. This factor was found to be the most significant factor in terms of explaining variance in the data. For instance, the first factor was able to explain 29.82% variance in the data. It was observed that respondents have positive perceptions of retirement analytics being used in their organizations. Respondents believed that HR analytics used in the banks could measure the annual turnover of employees and predict both involuntary and voluntary staff turnover rates. HR analytics can also assess each branch's retirement rate and determine the effectiveness of retaining high performers in banks. The following table 4.50 includes factor loadings of statements that were loaded onto ‘retirement analytics’. Figure 4.19 represents scree plot of Retention.

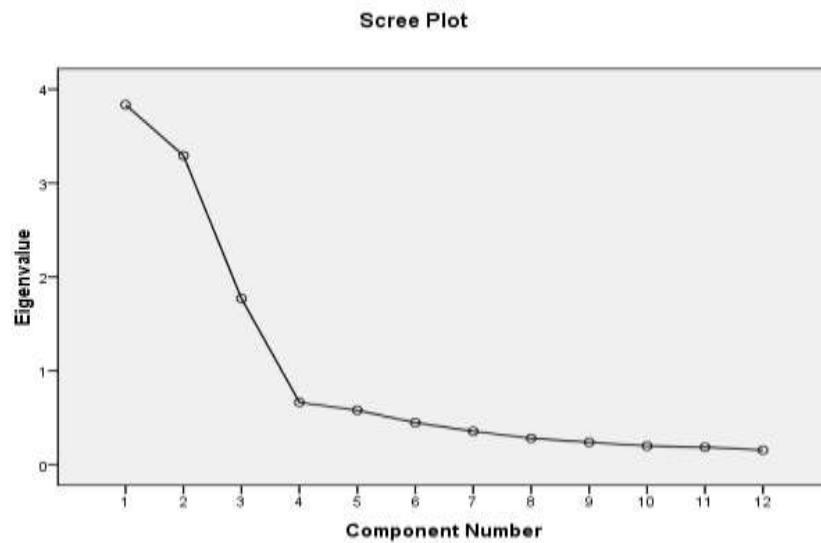


Figure 4.20: Scree plot of Retention

Findings of EFA on 12 statements on employee attrition in select banks produced three factors, and the second factor was named as ‘service analytics’, which included five statements. This factor was found to be the second most significant factor in terms of explaining variance in the data. For instance, this factor was able to explain 29.26% variance in the data.

Table 4.50: Factor loadings of statements under ‘retirement analytics’

Statements	Factor loadings
The average retirement rate is determined for each branch	.893
There is a system to predicting voluntary staff turnover rate in the organization (higher studies, stay-at-home parents, relocation)	.891
There is a system to predict the involuntary staff turnover rate in organization (layoffs and dismissal)	.867
This organization determines effectiveness of process to retain high performers	.815
This organization measures the annual turnover of employees in key positions in branches	.723
Variance explained	29.82%
Reliability of the scale (Cronbach alpha)	.896
Source: Authors’ Calculation	

In addition, the findings highlighted that banks have been using HR analytics to keep track of average service length by all employees by region and by function etc. The following table includes factor loadings of statements that were loaded onto ‘service analytics’:

Table 4.51: Factor loadings of statements under ‘service analytics’

Statements	Factor loadings
This organization determines the average length of service by function	.905
This organization determines the average length of service by region	.900
The average years of experience is determined for each branch in this organization	.853
This organization keeps track of the average length of service for its staff	.833
There is a system to assess the reasons why employees leave the organization	.657
Variance explained	29.26%
Reliability of the scale (Cronbach alpha)	.886
Source: Authors’ Calculation	

Findings of EFA on 12 statements on employee attrition in select banks produced three factors, and the third factor was named ‘comparative turnover analytics’, which included two words. This factor was found to be the third most significant factor in terms to explaining variance in the data. The following Table 4.52 includes factor loadings of statements that were loaded onto third factor ‘comparative turnover analytics’:

Table 4.52 Factor loadings of statements under ‘comparative turnover analytics’

Statements	Factor loadings
This organization determines staff turnover compared with market benchmark in every fiscal year	.943
There is a system to track employee turnover of best performers in every fiscal year	.940
Variance explained	15.08%
Reliability of the scale (Cronbach alpha)	.880
Source: Authors’ Calculation	

4.5.4.2 Effect of various types of HR analytics on employee retention

Structural Equation Modeling through AMOS has been used to analyze effects of descriptive, predictive, predictive, and predictive analytics on Retirement, service, and comparative turnover analytics. Hypothesized relationships are presented through path diagrams in structural equation modeling. For example, the figure 4.20 shows the relationship between HR analytics and retention. It consists of three exogenous variables, ‘Descriptive analytics’, ‘Predictive analytics’, and ‘Prescriptive analytics’ and three endogenous variables, ‘retirement analytics,’ ‘service analytics’ and ‘comparative turnover analytics’, as endogenous variables.

Table 4.53: Identification of Factors

Types of HR analytics	Factors of employee retention
Descriptive analytics	Retirement analytics
Prescriptive analytics	Service Analytics
Predictive analytics	Comparative turnover analytics

Table 4.54: Hypotheses proposed to examine the effect of various types of HR analytics on employee retention in banks

Sr. No.	Proposed hypotheses	Relationship
H30	Higher the use of descriptive analytics; greater is the use of retirement analytics in select banks	DA→RA (+)
H31	Higher the use of descriptive analytics; greater is the use of service analytics in select banks	DA→SA (+)
H32	Higher the use of descriptive analytics; greater is the use of comparative turnover analytics in select banks	DA→CTA (+)
H33	Higher the use of prescriptive analytics; greater is the use of retirement analytics in select banks	Pres_A→RA (+)
H34	Higher the use of prescriptive analytics; greater is the use of service analytics in select banks	Pres_A→SA (+)
H35	Higher the use of prescriptive analytics; greater is the use of comparative turnover analytics in select banks	Pres_A→CTA(+)
H36	Higher the use of predictive analytics; greater is the use of retirement analytics in select banks	Pred_A→RA (+)
H37	Higher the use of predictive analytics; greater is the use of service analytics in select banks	Pred_A→SA (+)

H38	Higher the use of predictive analytics; greater is the use of comparative turnover analytics in select banks	Pred_A→CTA(+)
Note: DA: descriptive analytics; Pres_A: prescriptive analytics; Pred_A: predictive analytics; RA: retirement analytics; SA: service analytics; CTA: comparative turnover analytics		
Source: Authors' calculation		

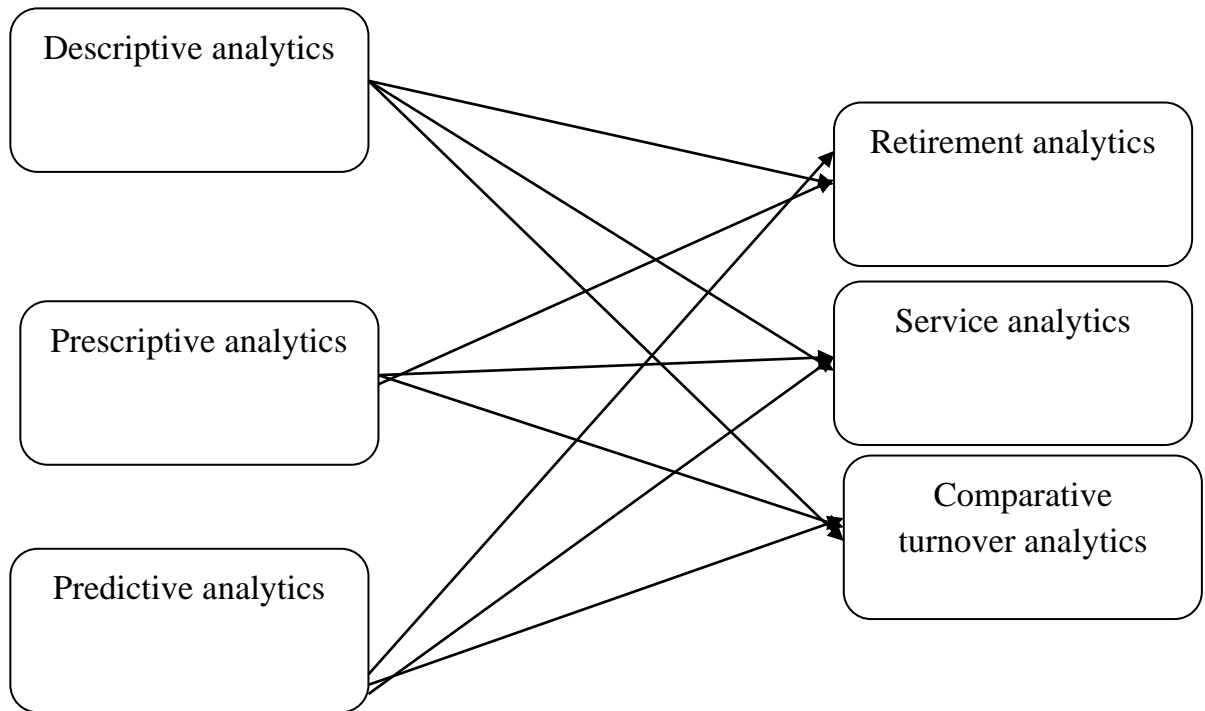


Figure 4.21 : The conceptual model for examining the effect of various types of HR analytics on employee retention in select banks

In the above table 4.54; the ‘+’ sign shows a positive linear relationship among variables. Drawing on these hypotheses, the present study developed a conceptual model as given in the following figure. Moreover, confirmatory factor analysis (CFA) was applied on the measurement model; reliability and validity of the model were also examined.

4.5.4.3 Testing measurement model ‘the effect of various types of HR analytics on employee retention in banks’

The measurement model was tested for both reliability and validity. The statistics pertaining to reliability and validity were obtained using confirmatory factor analysis (CFA) in AMOS. The information in this regard is given as under.

4.5.4.4 Reliability of the constructs

A construct is reliable if it generates similar results over time, given that conditions of measurement remain the same. The reliability of the constructs in the model was

tested with the help of ‘composite reliability’, denoted by CR in the below table. Composite reliability (CR) for each construct was greater than 0.70, a minimum cut-off value for constructs to be reliable (Nunnally, 1978). Therefore, it is concluded that the constructs used in the measurement model were reliable.

4.5.4.5 Validity of the constructs

The validity of a construct refers the degree to which a construct measures what it is supposed to measure.

Table 4.55: Statistics showing the reliability and validity of the model

	CR	AVE	SA	DA	Pred_A	Pres_A	RA	CTA
SA	0.893	0.631	0.794					
DA	0.888	0.616	0.110	0.785				
Pred_A	0.845	0.522	0.066	0.504	0.722			
Pres_A	0.831	0.565	-0.108	0.409	0.388	0.752		
RA	0.898	0.642	-0.033	0.023	0.039	0.114	0.801	
CTA	0.908	0.833	-0.119	-0.020	-0.012	-0.105	0.052	0.913

Note: DA: descriptive analytics; Pres_A: prescriptive analytics; Pred_A: predictive analytics; RA: retirement analytics; SA: service analytics; CTA: comparative turnover analytics; CR represent composite reliability; and AVE represent Average variance extracted

The present study tested two types of validity: convergent and discriminant. First, convergent validity refers to the degree to which two or more measures are related to a construct. This finding reveals that there is convergent validity among the scales used. The correlations between constructs (off-diagonal values) were found to be less than the square root of AVE (diagonal values). These findings supported the discriminant validity of the constructs used in the model. Moreover, every item under a specific construct was found to have factor loading greater than 0.5 (Fornell & Larcker, 1981).

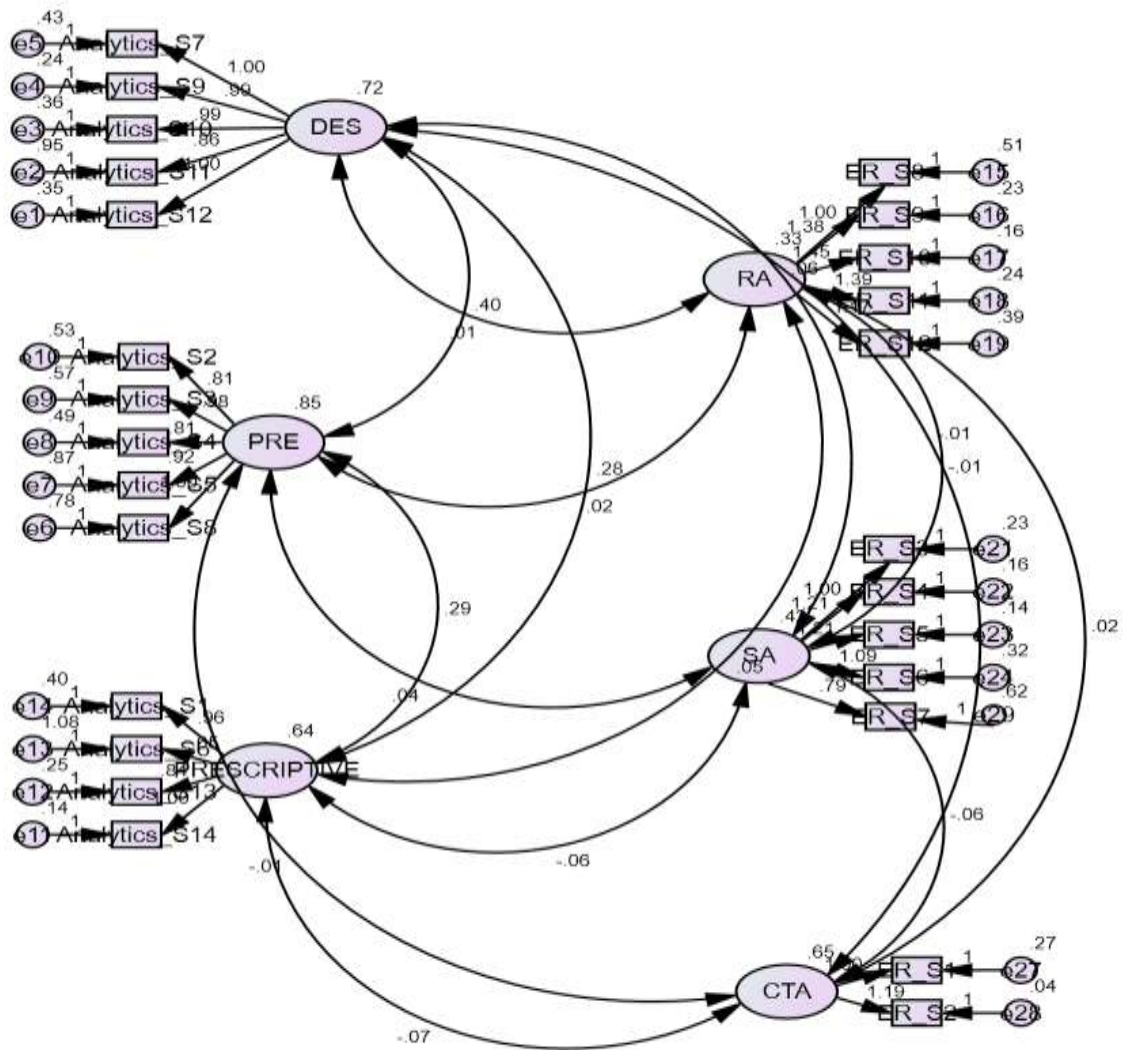


Figure 4.22: The path diagram for the hypothesized relationship of descriptive analytics, predictive analytics and prescriptive analytics, retirement analytics, service analytics and comparative turnover analytics.

Further, results indicate an acceptable fit of the measurement model as various statistics supported fit of the measurement model, as given in the table 4.56.

Table 4.56: Fit indices of the measurement model ‘the effect of various types of HR analytics on employee retention in banks’

Sr. No.	Indices with value	Recommended value	Reference
1	Chi-square=839.368, $p < 0.001$; dof=284; chi-square/dof=2.956	chi-square/dof < 3	Hair et al., 2006
2	Goodness of fit (GFI) = 0.86	GFI > 0.8	Baumgartner & Homburg, 1996
3	Comparative Fit Index (CFI) = 0.908	CFI > 0.9	Hair et al. 2006
4	Tucker-Lewis Index (TLI) = 0.909	TLI > 0.9	Hair et al. 2006
5	Root Mean Square Error of Approximation (RMSEA) = 0.07	RMSEA < 0.08	Steiger, 1990
Note: dof: degrees of freedom			
Source: Authors’ calculation			

Findings highlighted that the statistics given in the above table meet the specified criteria given by different authors. Therefore, the present measurement model is adequately fit.

4.5.4.6 Testing structural model ‘the effect of various types of HR analytics on employee retention in banks’

The present study proposed nine hypotheses to examine the effect of various types of HR analytics on employee retention in banks. These hypotheses were empirically tested with the help of SEM. Findings in this regard are mentioned in the following table 4.57.

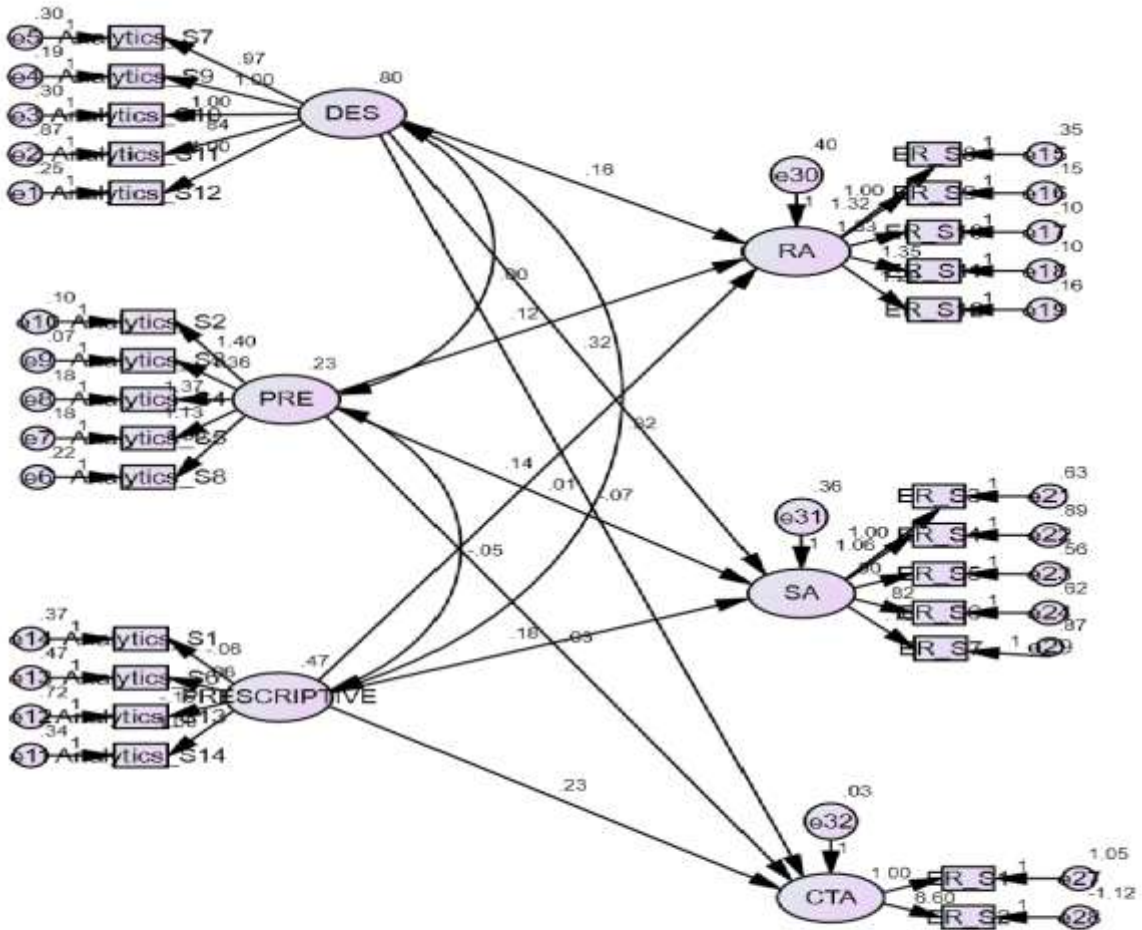


Figure 4.23: The path diagram for the hypothesized relationship of descriptive analytics, predictive analytics and prescriptive analytics, retirement analytics, service analytics and comparative turnover analytics.

Table 4.57: Results of the structural model: ‘the effect of various types of HR analytics on employee retention in banks’

Sr. No.	Proposed hypotheses	Relationship	Estimate (β)	t value	p value
H30	Higher the use of descriptive analytics; greater is the use of retirement analytics in select banks	DA \rightarrow RA (+)	0.228	3.587	0.000*
H31	Higher the use of descriptive analytics; greater is the use of service analytics in select banks	DA \rightarrow SA (+)	0.409	5.737	0.000*
H32	Higher the use of descriptive analytics; greater is the use of comparative turnover analytics in select banks	DA \rightarrow CTA (+)	0.275	1.55	0.121
H33	Higher the use of prescriptive analytics; greater is the use of retirement analytics in select banks	Pres_A \rightarrow RA (+)	0.148	2.293	0.022*
H34	Higher the use of prescriptive analytics; greater is the use of service analytics in select banks	Pres_A \rightarrow SA (+)	0.173	2.511	0.012*
H35	Higher the use of prescriptive analytics; greater is the use of comparative turnover analytics in select banks	Pres_A \rightarrow CTA(+)	0.871	1.693	0.090**
H36	Higher the use of predictive analytics; greater is the use of retirement analytics in select banks	Pred_A \rightarrow RA (+)	0.088	1.657	0.098**
H37	Higher the use of predictive analytics; greater is the use of service analytics in select banks	Pred_A \rightarrow SA (+)	0.009	0.168	0.866
H38	Higher the use of predictive analytics; greater is the use of comparative turnover analytics in select banks	Pred_A \rightarrow CTA(+)	0.069	1.239	0.215

* Significant at 5 percent level of significance; ** Significant at 10 percent level of significance

Notes: DA: descriptive analytics; Pres_A: prescriptive analytics; Pred_A: predictive analytics; RA: retirement analytics; SA: service analytics; CTA: comparative turnover analytics.

Source: Authors’ calculation

Based on the standardized coefficient, prescriptive analytics (0.871) is the most influencing path in the SEM model, followed by descriptive analytics (0.409) and predictive analytics is the least influencing variable (0.009). The results of the model are used to examine the hypothesized relationship between variables: Descriptive analytics and retirement analytics; descriptive analytics and service analytics; descriptive analytics and comparative turnover analytics; predictive analytics and retirement analytics; predictive analytics and service analytics; predictive analytics and comparative turnover analytics; prescriptive analytics and retirement analytics; prescriptive analytics and service analytics; prescriptive analytics and comparative turnover analytics.

H30: Higher the use of descriptive analytics; greater is the use of retirement analytics in select banks

The connecting path between descriptive analytics and retirement analytics yields Beta value= 0.228, Critical ratio=3.587, which is statistically significant as P-value <0.05 which means higher the use of descriptive analytics; greater is the use of retirement analytics in select banks. Thus, H30 is accepted

H31: Higher the use of descriptive analytics; greater is the use of service analytics in select banks

The connecting path between descriptive analytics and service analytics yields Beta value= 0.409, Critical ratio=5.737, which is statistically significant as P-value <0.05 which means higher the use of descriptive analytics; greater is the use of service analytics in select banks. Thus, H31 is accepted

H32: Higher the use of descriptive analytics; greater is the use of comparative turnover analytics in select banks

The connecting path between descriptive analytics and comparative turnover analytics yields Beta value= 0.275, Critical ratio=1.55, which is statistically not significant as P-value >0.05 which means higher the use of descriptive analytics; lesser is the use of comparative turnover analytics in select banks. Thus, H32 is not accepted

H33: Higher the use of prescriptive analytics; greater is the use of retirement analytics in select banks

The connecting path between prescriptive analytics and retirement analytics yields Beta value= 0.148, Critical ratio=2.293, which is statistically not significant as P-value >0.05 which means higher the use of prescriptive analytics; lesser is use of retirement analytics in select banks. Thus, H33 is not accepted

H34: Higher the use of prescriptive analytics; greater is the use of service analytics in select banks

The connecting path between prescriptive analytics and service analytics yields Beta value= 0.173, Critical ratio=2.511, which is statistically not significant as P-value >0.05 which means higher the use of prescriptive analytics; lesser is use of service analytics in select banks. Thus, H34 is not accepted

H35: Higher the use of prescriptive analytics; greater is the use of comparative turnover analytics in select banks

The connecting path between prescriptive analytics and comparative turnover analytics yields Beta value= 0.871, Critical ratio=1.693, which is statistically not significant as P-value >0.05 which means higher the use of prescriptive analytics; lesser is use of comparative turnover analytics in select banks. Thus, H35 is not accepted

H36: Higher the use of predictive analytics; greater is the use of retirement analytics in select banks

The connecting path between predictive analytics and retirement analytics yields Beta value= 0.088, Critical ratio=1.657, which is statistically not significant as P-value >0.05 which means higher the use of predictive analytics; lesser is use of retirement analytics in select banks. Thus, H36 is not accepted

H37: Higher the use of predictive analytics; greater is the use of service analytics in select banks

The connecting path between predictive analytics and service analytics yields Beta value= 0.009, Critical ratio=0.168, which is statistically not significant as P-value >0.05 which means higher the use of predictive analytics; lesser is use of service analytics in select banks. Thus, H37 is not accepted

H38: Higher the use of predictive analytics; greater is the use of comparative turnover analytics in select banks

The connecting path between predictive analytics and comparative turnover analytics yields Beta value= 0.069, Critical ratio=1.239, which is statistically not significant as P-value >0.05 which means higher the use of predictive analytics; lesser is use of comparative turnover analytics in select banks. Thus, H38 is not accepted.

4.6 Discussion on Results

Research gaps were identified that pointed towards the need for more understanding about the application of analytics in improving decision-making, due to which research questions were drawn based on an extensive literature review. In order to fulfill the objectives the study, a conceptual model was developed and tested empirically. The developed model examined the relationship between descriptive analytics, predictive analytics and prescriptive analytics and decision-making effectiveness in HR functions. Exploring HR analytics from an empirical standpoint appears has clear benefits. Some benefits include improved decision-making and better HR processes (Harrison and Getz, 2015; Hou, 2016; Ramamurthy et al., 2015).

In addition, empirical studies attempt to draw informative conclusions in HR analytics (Lazear, 2000; Fink, 2010; Hausknecht, 2014; Kandogan et al., 2014; Sharif, 2015).

Human resource analytics has become a relevant field in academics and practitioner-related research. The human resource analytics research is dominated by identified significant trends such as exploration of HR analytics as a strategic management tool, an evidence-based approach to HR analytics, HR analytics as effective decision making and the future of HR analytics. (Ben-Gal, 2019). The present study provides the analysis of results to decision makers for making intelligent decisions, contributing to the body of knowledge depicting HR analytics as effective decision making. The study's findings aim to support decision-makers by providing insights and consequently helping them to make better decisions.

The study focuses on the accomplishment of objective one; to examine the factors bringing out the need of HR analytics in select banks. Identifying factors enables the researcher to assess the importance of HR analytics in the sector. In order to find the need of HR analytics, Exploratory Factor Analysis (EFA) was applied to the current use of HR analytics items to identify the common factors that explain the order and structure of the measured variables. “Descriptive Analytics” is the first factor wherein three items correlated well with the factor including “current state of HR decisions

based on data analysis”, “access to different types of dashboards for decision making” and “HR policies are revised and updated based on data analysis” with factor loading values of .917, .879 and .821. The tools used in HR analytics in bank organizations mainly focus on descriptive analytics. Descriptive analytics transforms data into meaningful visualization and reports. Respondents agreed to use descriptive analytics for the revision and updation of HR policies. Bank managers have access to different dashboards for headcount analysis. The results reveals that visualization of people leaving and staying in the organization is done with the help of analytics specialist software.

Evans, 2016 support these findings; King, 2016 studies which studied adopting HR analytics. It has been found that the majority of organizations employ descriptive analytics. OrgVue, 2019 in their study found descriptive analytics used for headcount cost analysis and aggregating HR data. The tools used in HR analytics focus mainly on descriptive analytics (Saraswathy et al., 2017; Huselid, 2018).

“Predictive Analytics” is the second factor wherein two items correlated well with the factor, including “adequate use of analytics for decision making in the organization” and “data analytics for identification of individuals which need attention” with factor loading values of .873 and .816. Predictive analytics analyze historical data and identify patterns in the data. Respondents agreed that banks increasingly used predictive analytics to inform human resource decisions such as workforce requirements and HR demand. In addition, banks use predictive analytics tools to identify individuals needing attention. Respondents agreed with predictive analytics that forecasts organizational function's most significant impact on the bottom line and performance levels. Bassi, 2011 support the findings; Molefe 2013; Baasi et al., 2015, which stated HR analytics perform optimize the workforce to generate a better return on investment (ROI). Predictive analytics enables organizations to analyze past data and develop insights into critical factors related to voluntary termination, absenteeism and risks, Mishra et al., 2016. The present study reveals factors such as the identifying at-risk individuals, function impacting bottom line and performance levels enabled by predictive analytics. In their study Jabir et al., 2019 identified predictive analytics deployed by human resource practitioners facilitates in predicting organizational problems in advance, such as to enhance productivity and minimize risks.

“Prescriptive Analytics” is the third factor wherein two items correlated well with the factor, including “application of analytics has integrated use across organization for HR functions” and “shift to data based decisions has proved to be effective in this organization” with factor loading values of .773 and .749. The results indicate that prescriptive analytics has integrated use in the organization and aids organizations in drawing specific recommendations. Respondents agreed that shift to data-based decisions proved effective in the organization. The advanced HR analytics tool enables the organization to monitor organizational health and adapt the workforce to changes in business environment. The findings are supported by Berk et al., 2019 study that developed an optimization-based framework in hiring to improve human resource planning by estimating staffing needs in the first stage and completing the project assignments in the second stage. Kale et al., 2022 in their study on HR analytics and organization performance, found predictive analytics aids in employee hiring based on required skills, knowledge and employee life cycle.

The need for HR analytics depends on factors such as descriptive analytics (understanding the past and current state of HR decisions), predictive analytics (predicting future HR decisions), and prescriptive analytics (HR decisions proved to be effective). Therefore, identifying HR analytics factors enables the function to leverage the benefits of analytics and further assist in data-driven decision-making.

The second research question answered in this study is the role of HR analytics on decision-making in HR functions tested through regression analysis. An attempt is made to study the relationship between HR analytics factors and decision-making in HR and determine how HR analytics is helpful in decision-making in HR functions. The analysis done in the study confirms role of HR analytics in decision-making. The values from the output table (4.12) reveal that HR analytics significantly influences decision-making effectiveness in HR functions. Regression is applied to study the role of HR analytics on decision-making in HR.

The model supports with obtained R-value .495 and R square .245, the results supports that if HR analytics is used it will help in improving decision-making.

The hypotheses (H1) framed stating that Descriptive analytics in a bank significantly influenced the effectiveness of decision-making in HR functions ($\beta = 0.176$; $p < 0.05$) was accepted. It means that the higher the intensity of using descriptive analytics in a

bank, the greater is the effectiveness of decision-making in HR functions. Hypotheses (H2) framed stating prescriptive analytics significantly influencing the point of decision-making in HR functions ($\beta = 0.241$; $p < 0.000$) was accepted. The finding suggested that prescriptive analytics in a bank plays a vital role in the effectiveness of decision-making in HR functions. Hypotheses (H3), framed that using predictive analytics in a bank significantly influences decision-making effectiveness in HR functions. The hypothesis was supported as predictive analytics resulted in a higher significance of decision-making in HR functions ($\beta = 0.395$; $p = 0.01$). Factors such as 'predictive analytics' were the strongest predictor of decision-making effectiveness in HR functions. The above findings are supported by Hussain et al. 2013 study, which found that visualization and data analytics enhance decision-making and knowledge discovery. The methodology was a case study approach wherein data was presented in analytics and visualization-supported decision-making.

Based on the findings on role of HR analytics, 'predictive analytics' emerged as the strongest predictor of decision-making in HR functions. Therefore, predictive analytics enables HR to examine future insights into their functions, such as recruitment, training and development, performance management, and retention. Predictive analytics assists managerial people in decision-making about recruiting talented people, placing people in suitable training and development, performance management, and employee retention. The findings on the role of HR analytics in decision-making in HR functions will reinforce the importance of HR analytics. Sharma et al., 2022 focused on descriptive, predictive, and prescriptive analytics, encompassing the ability to answer different queries and their role in strategic business management.

The third research question answered in this study is the effect of HR analytics on identified HR functions. Human resource functions are recruitment, training and development, performance management, and retention. HR analytics includes descriptive, predictive and prescriptive analytics. While investigating the hypotheses for recruitment function; the findings of this study demonstrated that HR analytics; descriptive analytics, prescriptive analytics, and predictive analytics are significantly related to updated recruitment and ease of recruitment. During the investigation of the hypotheses for the training and development function, findings of the study reveals

that descriptive analytics is significantly related to post-training analytics and financial analytics of training; prescriptive analytics is significantly related to financial analytics of training and training for skill gap; predictive analytics is related substantially to post training analytics. Finally, while investigating the hypotheses for performance management, the study's findings demonstrated that descriptive analytics is significantly associated with skill competency analytics and promotion competency analytics; prescriptive analytics is related considerably to skill competency analytics and satisfaction and productivity analytics. The study's findings, which examined the retention hypotheses, showed that descriptive analytics is strongly associated with retirement and service analytics.

Chapter-5

Recommendations, Implications and Conclusion

The chapter deals with a summary, the study's conclusion, managerial implications, limitations and recommendations.

5.1 Summary

The study focuses on the human resource analytics role in decision-making in select banking organizations. The introduction chapter of the thesis describes the significance of study, research objectives, and description of the study's independent variable, including human resource analytics, which consists of descriptive analytics, predictive analytics and prescriptive analytics. The dependent variable of the study is human resource decision-making. The decision-making will be in the context of human resource functions such as recruitment, training and development, performance management and retention.

The literature review chapter consists of an extensive literature review from 2003 to 2023 to examine the role of Human Resource Analytics in Human Resource Decision Making in the banking sector in Punjab. The studies were related to Human Resource Analytics and Human Resource Decisions. As per the study conducted by Higgins J., Cooperstein G, and Peterson M. (2011), analytics aids an organization in developing a workforce strategy linked with business strategy by improving the retention of key talent and thereby increasing the efficiency and productivity of the workforce. HR analytics allows organizations to enhance workforce efficiency with the help of gathering information and utilizing the data, making much better choices and procedures. HR analytics links company information and individual information to display the effect HR has on an organization and make ways to enhance results.

Rouse M (2012) stated that HR analytics is a well-informed use of information mining and small business analytics strategies for human learning resource information. HR analytics offers a perspective for efficiently handling its workers to obtain company objectives quickly and efficiently. HR analytics determine what information to model as well as predict. Therefore, the companies can get Return on Investment (ROI) on their human capital. Bersin (2015), in research recognized by "Global Human Capital Trends 2015" surveyed more than 3,300 companies and HR

frontrunners by hundred six places and concluded that analytics is the most distinct skill experiencing their business.

Bersin (2016), in their research "Global Human Capital Trends 2016" reports that analytics is a vital concern to the organization. HR executives dealing with personal analytics will benefit from their competitors and locate themselves along the winning aspect within the worldwide skill competitors. In their research, Sjoerd van den, Tanya Bondarouk (2016) enlightened the long term programs, structure, value, and method of HR analytics. HR analytics supports determining and quantifying people's data with company data.

The research methodology chapter consists of the following objectives:

- a. To examine the factors bringing out the need of HR analytics in select banks
- b. To study the role of HR analytics on decision making in HR functions
- c. To measure the effect of different types of analytics on identified HR functions

In order to achieve the stated objectives; the population, research design, sampling technique, data collection, research instrument and statistical analysis approach had been explained. A descriptive research design and stratified sampling technique were used to select respondents from the banking sector. The respondents were drawn from Bank of Baroda, Bank of India, Canara Bank, Punjab National Bank, State Bank of India in Public sector and Axis Bank, HDFC Bank, ICICI Bank, Kotak Mahindra and YES Bank from Private sector in Punjab, from 22 districts. Data is collected using a structured questionnaire with four sections. A total of 14 statements are considered to examine factors that bring out the need of HR analytics. Ineffectiveness of human resource function statements include related to overall performance of HR department, well-defined roles and responsibilities of HR department; the HR department adds value to the business and preferred existing working style (Barney and Wright, 1998). For identified HR functions, the recruitment function consists of 14 statements, the training and development function consists of 14 statements, performance management consists of 12 statements and retention consists of 12 statements. The Likert scale has been used to record responses from respondents.

The data analysis and interpretation chapter revealed that the application of human resource analytics exists in most Public and Private Banks. Exploratory Factor Analysis (EFA)'s findings produced three factors: 'Descriptive analytics', 'Predictive analytics' and 'Prescriptive analytics'. The influence of HR analytics on decision-making in human resource functions using multiple linear regressions has been identified.

The findings revealed that from all the factors related to HR analytics, predictive analytics resulted in higher decision-making effectiveness in HR functions ($\beta = 0.405$; $p=0.01$). The findings indicated that the higher the intensity of using predictive analytics in a bank, the greater the effectiveness of decision-making in HR functions. The effect of types of analytics on identified HR functions is identified using structural equation modelling. The findings revealed that descriptive analytics is significantly related to post training analytics and financial analytics in training function; prescriptive analytics is significantly related to financial analytics of training and skill gap training; predictive analytics is significantly related to post training analytics.

Descriptive analytics is related substantially to skill competency and promotion competency analytics; prescriptive analytics is related to skill competency analytics and satisfaction and productivity analytics. Finally, descriptive analytics is significantly related to retirement and service analytics.

5.2 Major Findings

The study aims to examine need and role of HR analytics on human resource decision making and further to see the effect of HR analytics on identified HR functions.

- a. The study's findings revealed three factors bringing out the need for HR analytics in select banks: 'Descriptive analytics', 'Predictive analytics' and 'Prescriptive analytics'.
- b. Factor-wise influence of HR analytics factors on decision-making in HR functions was found to be significant. The factor 'predictive analytics' was found to be the strongest predictor of the effectiveness of decision-making in HR functions.

- c. HR analytics effects recruitment function with components of descriptive analytics, predictive analytics and prescriptive analytics in the banks. The finding revealed prescriptive analytics (0.598) is the most influencing path followed by descriptive analytics (0.307) based on the standardized coefficient.
- d. HR analytics effects training and development function with descriptive analytics, predictive analytics and prescriptive analytics in the bank. The finding revealed prescriptive analytics (1.011) is the most influencing path, followed by descriptive analytics (0.389) based on a standardized coefficient.
- e. HR analytics effects performance management function with descriptive analytics, predictive analytics and prescriptive analytics in bank. The finding revealed that prescriptive analytics (1.015) is the most influencing path, followed by descriptive analytics (0.442) based on standardized coefficient.
- f. HR analytics effects retention function with descriptive analytics, predictive analytics and prescriptive analytics in the bank. The finding revealed that descriptive analytics (0.409) is the most influencing path based on the standardized coefficient.

5.3 Research Implications

Literature supports analytics aids in the organizational decision-making process by demonstrating analytics solutions leading to better and more accurate decisions. Therefore the importance of data-driven decisions is highly recommended. Business organizations implement HR analytics to facilitate top management in making data-based and reliable decisions. The need for a unified platform of meaningful data and analytics used by human resources to drive human resource strategy exists. HR analytics assists in understanding and identifying talent needs, training and development, management of performance and retaining top performers. The present study explores the role of HR analytics, such as descriptive analytics, predictive analytics and prescriptive analytics, in human resource decision making. From the perspective of improved decision making, the study will add value to the banking and financial sector.

- a. There needs to be more empirical research relating to the role of HR analytics in human resource decision-making in the banking sector in Punjab.
- b. Most studies examine the relationship between HR analytics and organizational effectiveness, challenges and factors to adoption, understanding, and detangling the concept of HR analytics. In the present research, the researcher tries to investigate the role of HR analytics on human resource decision-making and measure its effect on human resource functions.
- c. As per the researcher's knowledge, this is the first attempt to integrate the need for HR analytics, decision-making in HR functions, and the effect of HR analytics on identified HR functions.
- d. The findings obtained from the research work apply to retail bank employees' working in human resource and senior managerial positions.
- e. Major studies in the past had been restricted to applying HR analytics in the Information Technology and ITES sector in developed economies, specifically USA and UK (Harris et al., 2011). The present study aimed to explore the human capital measurement from the population in the banking industry.
- f. Future prospects of HR analytics include a significant contribution towards the decision-making in organizations. The application of analytics can transform organizational models by examining employee attributes and skills during consolidations and mergers.

5.4 Managerial Implications

The study has several implications for key stakeholders such as HR managers, HR leaders and consulting practitioners, CEOs, academia, and policymakers. The study contributes by developing reliable insights into the unexplored research area in the context of human resource decision-making in the banking sector in Punjab.

The research findings have substantial implications for human resource practitioners and managers working in the banking industry at the state and national levels.

- a. The findings enable HR managers to understand HR analytics for informed human resource decision-making and further development of the HR analytics function.

- b. HR practitioners in banking will practice maintaining an optimum balance between attracting technologically skilled talent and designing the training program for existing employees facing changing role requirements. The effect of analytics on the recruitment function facilitates hiring the “best fit” for bank jobs, yielding better quality recruits with prescriptive and descriptive analytics application.
- c. The analytics abilities of many HR professionals need to be improved and more extensive to carry out the process of HR analytics. Therefore analytics skills such as descriptive, predictive and prescriptive analysis to make intelligent decisions will be emphasized for HR employees in bank organizations for its successful application.
- d. The positive results obtained through analysis show the need to invest in training managerial-level employees to perform HR analytics to make human resource decisions efficiently and effectively. In addition, training in statistical methods is essential for converting data into meaningful insights. (Reddy and Lakshmikeerthi, 2017).
- e. The study's findings revealed that the higher the intensity of using predictive analytics in bank organizations, greater the effectiveness of decision-making in HR functions. With predictive analytics, bank organizations get measurable outcomes to manage functions such as recruitment, training and development, performance management and retention, increasing productivity of the entire organization.

5.5 Limitations of the study

While conducting the research work, several challenges were faced by the researcher: Apart from time constraints and restricted sample size, several others contributed towards the limitations of the study:

- a. The study is confined to one sector, and few samples are selected among the population. The study is conducted with only 400 managerial level employees as a single source of data, ignoring others. The selected sample consists of retail, circle and zonal bank branches.

- b. The study is based on the perception of employees which may be subject to change with passage of time. Personal bias and possible reluctance to disclose information due to HR function seen as a confidential matter may have affected the results of this study
- c. During the collection of data in retail, circle and zonal bank branches the managers were found occupied with staff and customers. Asking those Managers to spare their time in their busy schedule was very challenging. Moreover, the researcher needed help in acquiring information from Punjab National Bank Zonal branch, Amritsar as they had extreme security measures and were reluctant to share any information without proof.
- d. Due to less availability of select banks; Bank of Baroda (Public) and Kotak Mahindra Bank (Private) in Doaba and Malwa regions, the researcher found comparatively less respondents from these banks.
- e. The external factors such as social, cultural, economical and legal not considered may affect the variables under study. Therefore, the results are not definitive.

5.6 Recommendations

- a. It is suggested to advance research in the effective utilization of HR Analytics in decision-making for the banking sector. More studies on a broader scale need to be conducted on using and applying HR Analytics in the banking sector using a larger pool of respondents outside Punjab.
- b. The findings reveal banks rely primarily upon descriptive analytics because key function of finance is reporting. Banks should adopt a forward-looking approach and build insights into what may happen instead of describing what has already occurred.
- c. It is suggested that HR practitioners in banks imbibe a clear and accurate understanding of how people may use technology in their jobs and benefits and outcomes from analytic tools that may be provided. This intervention can shape employee engagement for delivering a superior customer experience.

- d. The application of predictive analytics in the retention function will lead to a reduction in turnover and loss of organizational intelligence.
- e. A decision-making framework model is suggested to be implemented as future scope for managerial decision-making in banks. In addition, advanced analytics models and algorithms can be employed to create dashboards providing human resource managers and project managers with real-time and quantitative information.
- f. HR professionals source for tech savvy and analyze data in other departments; therefore, the same approach must be adopted while hiring HR professionals. HR Analytics can be a separate domain to be used in making right investment decisions for hiring and retaining efficient employees in the banking sector.
- g. To gain a competitive advantage in HR decision-making, leadership must understand that the necessary tools, techniques, data and resources must be made available to HR professionals to enhance decision-making.

5.7 Conclusion

Human resource plays a significant part in business results, and using fact-based information is critical in business decision-making. The financial services industry is experiencing collaborative efforts between human resource function and finance to prepare data-driven recommendations and plan. The present study reveals that most bank organizations have favored HR Analytics applications. As a result, bank organizations can track their functions with the help of human resource metrics.

The metrics evaluate recruitment, training and development, performance management and retention. Recruitment metrics track number of vacancies and quantity recruited, number of people interviewed, time to recruit, quality of recruits, first-year turnover etc. Training and development metrics track duration of annual training hours undergone by employees, spend per employee on training and development, percentage of employees with development plan, spend on training as a proportion of profit, investment in training as percentage of sales, learning and development investment per full time employee etc. For employee performance management, the bank organizations deployed metric to track the average time to promotion, satisfaction of new hires, percentage of staff working at acceptable

performance level, effectiveness of performance management process etc. Retention metrics tracks the staff turnover compared with market benchmark, turnover of high performers, average length of service, average length of experience, retention rate, turnover of employees in key positions etc. Bank managers have favoured that there exists a system to assess reasons for employees leaving the organization. The study's findings reveal identifying factors influencing the need for HR analytics.

'Predictive analytics' was identified as one factor affecting the need for HR analytics, resulting in higher decision-making effectiveness in HR functions. Predictive analytics is adequately used for decision-making in banks and banks use for identification of individuals which need attention. Further, banks were also found to use predictive analytics to identify departments needing attention and determine specific organizational functions having the most significant impact on the bottom line. Organizations can optimize HR functions and other business decision-making through proper data management and analysis. The study findings allow organizational leaders to understand human resource decisions yielding higher returns using HR Analytics.

The organizational purpose of resolving their people-related challenges could be accomplished by identifying factors influencing human resource decision-making. The quality of decisions gets improved with the application of HR Analytics. The study's findings provide the need to build a robust HR Analytics team to support evidence-based decision-making of human resources that requires new strategies for attracting, developing, and retaining key talent.

The methodology adopted for conducting the study included a quantitative survey. The respondents were drawn from select Public and Private Banks in Punjab. The research instrument consists of questions about recruitment training and development, performance management, retention and decision-making. The research design taken was descriptive to understand the adoption of HR Analytics. The method of sampling constituted stratified random sampling. The scaling technique used for the development of the questionnaire is nominal scale, seven point Likert scale type. The researcher used factor analysis, multiple regression analysis, structural equation modelling, averages, percentage graphs, bar diagrams, and statistical package for social science (SPSS) version 20.0 to analyze data and outputs interpreted in current

study. In addition, these techniques were used to test the significance of set parameters. Although the research covered bank branches in Punjab, the results can be justifiably applied to branches nationwide.

The findings of the study may provide management practitioners valuable guidance. Managers may therefore establish appropriate techniques to form organizational human resource management strategies. The study provides recommendations on how analytics add value in the service sector decision-making, thus increasing awareness regarding the analytics' role in creating long-term value in the organization. The recommendations for future work include conducting survey research with respondents in public and private banking organizations and investigating the analytics applications that the banking sector intends to invest in and potential challenges caused.

A construct along with analytics influence on the quality of decisions could be added, which can measure the effect on decision makers' rationality and intuition. The role of human resource analytics in organizational culture needs to be examined. The study's finding provides data that provides actionable insights related to human resource functions with HR analytics. The application of analytics begins with clarity about decisions to be made, collection of correct data and choosing appropriate tools for effective decision-making. The motive of applying HR analytics should be towards the performance improvement and quantified return on investment.

5.8 Scope for Future Research

The research scenario on human resource analytics has evolved, providing room for new contributions aiming to define the field. The three areas of investigation: HR analytics enablers, applications, and value drivers may be used to express a potential research agenda for the development of the field in the upcoming years.

There is scope for further research in the application of blockchain and artificial intelligence in various segments of HR in banking, leading to performing comparative studies before and after implementing the technology. In addition, the study may be investigated HR analytics by applying advanced methodologies such as machine learning and algorithms.

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APPENDIX 1: Questionnaire

HR Analytics and HR Decisions in Select Banks of India

Dear Respondent,

My research topic is “HR Analytics and HR Decisions in Select banks of India”. Please carefully review all the below statements and indicate the response against the statement which most closely represents your opinion. I assure you that the information you provide will be kept strictly confidential and will be used for academic purposes only.

* Required

1. **Name ***
2. **Gender ***
3. **Email ***
4. **Contact No. ***
5. **Name of Organization ***
6. **Department ***
7. **Designation ***
8. **Qualification *: Graduate or Post Graduate**
9. **Experience *: a) 0-5,b) 6-10,c) 11-15 d) 16 or above**

Section- II

The respondents belong to the managerial category of employees in the banking sector of Punjab, India.

The respondents in the survey will be requested to respond to the following statements, in the scale given below:

1. Strongly Disagree; 2. Disagree; 3. Somewhat Disagree; 4. Neither Agree nor Disagree; 5. Somewhat Agree; 6. Agree; 7. Strongly Agree

Research Objective: To measure the effect of various types of analytics on identified HR functions

1. This organization's HR executive are aware about number of vacancies for recruitment.
2. This organization's human resource function maintains updated database for total manpower quantity recruited.
3. This organization determines internal hiring rate in every recruitment cycle.
4. This organization determines external hiring rate in every recruitment cycle.
5. This organization minimizes time to recruit in each recruitment cycle.
6. The applicants demonstrate adherence to ethical code during interview.
7. This organization tends to maintain higher offer acceptance rate in every recruitment cycle.
8. This organization reduces cost of recruitment in every cycle.
9. There is a system of tracking speed of hiring candidates in this organization.
10. There is a system to identify ease of recruitment on basis of organizational roles (Assistant Manager, Deputy General Manager, Chief General Manager).
11. There is a system to identify difficulty of recruitment on basis of organizational roles (Assistant Manager, Deputy General Manager, Chief General Manager).
12. This organization determines cost for hiring the external employee in the company.
13. This organization determines quality of recruits with their performance level.
14. There is a system for tracking first year turnover in this organization.
15. There is a system to track the duration of annual training hours undergone by employee.
16. This organization ascertains expenditure per employee on training and development.
17. This organization adopts initiatives for identification of priority skills gap.
18. This organization invest in training as a proportion of profit earned in a year.
19. This organization invests in training as a proportion of payroll provided in a year.
20. This organization invests in training as a percentage of revenue in a year.
21. This organization ascertains percentage of employees receiving training every year.

22. This organization ascertains percentage of employees with competency development plans in a branch.
23. A quantifiable measure to track learners' activity and value from training program is deployed by this organization
24. This organization keeps track of instances of misconduct resulting from inadequate training
25. This organization keeps a track of effectiveness of training programs.
26. A system for measuring participant satisfaction levels with training activities is deployed by organization
27. This organization determines improvement in performance post-training in each cycle.
28. This organization determines effectiveness of quality improvement post training in each cycle.
29. This organization determines the average time of employees' promotion in each fiscal year
30. This organization assess total promotions over total transfer rate in each fiscal year.
31. This organization prepares competency level skill inventory for each of its branch
32. There is a system to track satisfaction of new hires in this organization.
33. This organization determines percentage of staff working at acceptable performance level in every branch
34. This organization measures staff competencies to deliver business goals in every branch
35. This organization measures educational level of its staff at each hierarchical level in branch.
36. This organization determines effectiveness of performance management processes every fiscal year
37. This organization measures extent to which performance management are aligned to business goals.
38. There is a system to measure percentage of personnel development plans complying with business plans each year.
39. There is a system to measure percentage of personnel development plans achieved by functional area every year.

40. This organization has deployed productivity measures such as revenue per employee
41. This organization determines staff turnover compared with market benchmark in every fiscal year.
42. There is a system to track employee turnover of best performers in every fiscal year.
43. This organization keeps a track of average length of service for its staff.
44. This organization determines average length of service by region.
45. This organization determines average length of service by function.
46. The average years of experience is determined for each branch in this organization.
47. There is a system to assess the reasons why employees leave the organization.
48. This organization measures the annual turnover of employees in key positions in branches
49. There is a system to predict the involuntary staff turnover rate in organization (layoffs and dismissal)
50. There is a system to predicting voluntary staff turnover rate in organization (higher studies, stay-at-home parents, relocation)
51. The average retirement rate is determined for each branch.
52. This organization determines effectiveness of process to retain high performers.

Section- III

The respondents belong to the managerial category of employees in the banking sector of Punjab, India.

The respondents in the survey will be requested to respond to the following statements, in the scale given below:

1. Strongly Disagree; 2. Disagree; 3. Somewhat Disagree; 4. Neither Agree nor Disagree; 5. Somewhat Agree; 6. Agree; 7. Strongly Agree

Research Objective: To study the role of HR Analytics on decision making in HR functions

1. Overall, the HR department is performing its job the way it is expected to perform
2. The HR department has been able to meet expectations by executing its role and responsibilities in a well define manner

3. I believe that HR department adds value to our business activities
4. The HR department works in such a way that I would not like to see any change in its existing working style.

Section- IV

The respondents belong to the managerial category of employees in the banking sector of Punjab, India.

The respondents in the survey will be requested to respond to the following statements, in the scale given below:

2. Strongly Disagree; 2. Disagree; 3. Somewhat Disagree; 4. Neither Agree nor Disagree; 5. Somewhat Agree; 6. Agree; 7. Strongly Agree

Research Objective: To examine the factors bringing out the need of HR Analytics in select banks

1. The application of Analytics has integrated use across organization for HR functions.
2. This organization's current state of HR decisions is based on data analysis.
3. Bank managers' in this organization have access to different types of dashboards for decision making.
4. This organization's HR policies are revised and updated on the basis of data analysis.
5. HR Analytics is adequately used for decision making in organization
6. The shift to data based decisions has proved to be effective in this organization.
7. This organization uses HR Analytics for monitoring key standards of organizational health.
This organization use HR Analytics for identification of individuals which need attention
8. This organization use HR Analytics for identification of departments which need attention
9. This organization uses HR Analytics for determining which organizational functions have greatest impact on the bottom line.
10. This organization uses HR Analytics for forecasting performance levels.
11. This organization use HR analytics for learning why people stay in the organization.
12. This organization use HR analytics for learning why people leave the organization.
13. This organization use HR analytics for adapting workforce to changes in business environment

APPENDIX 2: Published Research Work

S.No	Title of paper with author names	Name of journal / conference	Published date	Issn no/ vol no, issue no	Indexing in Scopus/ Web of Science/UG C-CARE list (please mention)
1.	Analyzing Human Resource Practices for Decision Making in Banking Sector using HR Analytics	Materials Today Proceedings	February,2021	22147853	Scopus
2.	Decisions Making in HR: Application of HR Analytics	International Journal of Research and Analytical Reviews	April,2018	2348-1269	UGC Care

3.	A study of job satisfaction among managers in ICICI and HDFC Bank in Jalandhar	International Journal of Applied Business and Economic Research	July,2016	0972-7302	Scopus
4.	An Optimized HR Analytics Approach to Impact Decision Making Process in Banking Sector to increase employee performance	NeuroQuantology	December,2022	21/20	Scopus
5.	Employee's Intentions to Use HR Analytics: Technology Acceptance Model with Job Relevance	Vision: The Journal of Business Perspective	August, 2023	09722629231183540	ABDC

	and Self-Efficacy				
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APPENDIX 3: Papers presented in Conferences

Serial No.	Name of Conference	Author's Name	Indexed (WoS/Scopus/UGC/NAAS)	Year (MM/DD/YYYY)
1	7th International Joint Conference on Computing Sciences (ICCS-2023)	Tanya Nagpal Mridula Mishra	International Conference/Scopus indexed	05-05-2023 TO 05-05-2023
2	Business in a Turbulent World: Keeping Connection Alive	Tanya Nagpal Mridula Mishra	International Conference/Scopus indexed	22-11-2022 to 22-11-2022
3	Recent trends in Management and Social Sciences	Tanya Nagpal	National Conference/Scopus indexed	03-05-2021 to 03-06-2021
4	Rethinking Business: Designing Strategies in the Age of Disruptions	Tanya Nagpal Mridula Mishra	International Conference/Scopus indexed	19-12-2020
5	Business Agility in Volatile times	Tanya Nagpal	International Conference/Scopus indexed	11-07-2019 to 11-09-2019
6	Dynamics of Financial Sector Reforms	Shalini Shukla Tanya Nagpal	International Conference/Scopus indexed	04-06-2018 to 04-07-2018
7	Strategies for Global Competitiveness and Economic Growth	Tanya Nagpal	International Conference/Scopus indexed	03-17-2017 to 03-18-2017
8	10th Doctoral Thesis Conference	Tanya Nagpal		04-20-2017 to 04-21-2017
9	FORE International OB & HR Conference 2016	Kanika Garg Tanya Nagpal	International Conference/Scopus indexed	11-24-2016 to 11-25-2016
10	Global Trends in Teacher Education (GTTT-2016)	Kanika Garg Mridula Mishra Tanya Nagpal	International Conference/Scopus indexed	04-15-2016 to 04-16-2016
11	Strategies for Global Competitiveness and Economic Growth	Tanya Nagpal Mridula Mishra	International Conference/Scopus indexed	08-21-2015 to 08-22-2015

APPENDIX 4: Workshops Attended

S.No.	Title of Workshop	Organized By	Date
1	HR Analytics for Organizational Excellence	GL Bajaj Institute of Management & Research Greater Noida	19-02-2019
2	Online Workshop on HR Analytics	National Human Resource Development	22-06-2020 to 26-06-2020
3	Leveraging Analytics for Competitive Advantage	Viveknand Education Society Business School.	17-01-2022 to 21-01-2022
4	HR Analytics	New Horizons Research Group	27-08-2022 to 28-08-2022 3-09-2022 to 4-09-2022