European Economic Letters
ISSN 2323-5233
Vol 15, Issue 1 (2025)
http://eelet.org.uk

Banking Operations: The Strategic Role of Adopting Big Data Analytics by Bank Personnel of SBI and ICICI Banks

Dr. Chandrakala. L[1] dr.chandrak2019@gmail.com
Dr. Ravi Kiran Dharam Soth[2] dr.dsrk36@outlook.com

Abstract
Incorporating Big Data Analytics (BDA) has significantly transformed banking operations, enhancing efficiency, risk management, fraud detection, and customer engagement. This study analyses the impact of Big Data Analytics (BDA) adoption on operational dynamics in SBI and ICICI Banks, focusing on how bank personnel utilise data-driven insights to improve decision-making. This study utilised a stratified random sample of 418 bank employees of SBI and ICICI Bank personnel across essential functional domains such as risk assessment, fraud prevention, customer service, and data analytics to evaluate the transformative impact of Big Data Analytics (BDA).

A structured questionnaire was carefully designed to collect primary data, while secondary data was obtained from regulatory documents, financial statements, and industry reports. To ensure robustness, Cronbach's Alpha, the Kaiser-Meyer-Olkin (KMO) measure, and Bartlett's Test was utilised for assessing reliability and validity. Statistical techniques were used to extract significant insights, including factor analysis, correlation matrix, t-tests, ANOVA, and Chi-square tests. The findings highlight BDA's essential function in promoting operational excellence, improving predictive capabilities, and ensuring a competitive advantage for banks. This analysis underlines the association among technology adoption and banking efficiency, providing strategic recommendations for enhancing data-driven practices in modern financial institutions.

Key Words
Big Data Analytics (BDA), Banking Operations, Risk Assessment, Fraud Detection, Customer Segmentation, Financial Technologies, Operational efficiency, Analytics, Digital Transformation, Banking Innovation, AI, ML in Financial Firms.

Introduction

The banking industry is enduring an exemplary shift by improving operational efficiency, customer experience, and risk management via massive data analysis (Big Data Analytics, or BDA). According to Kumar and Sharma (2023)[3], Indian financial institutions, notably the State Bank of India (SBI) and the Bank ICICI, recognise the strategic value of BDA in decision-making, fraud detection, credit risk assessment, and personalised banking services. Conversely, the ability of banks to use big data technology effectively depends on their employees' transparency, adaptability, and skill (Gupta et al., 2022)[4]. The use of BDA technology in the financial sector refers to applying cutting-edge technologies and statistical methods to extract significant information from large data sets, including structured and unstructured data (McKinsey, 2021). As per Choudhury and Patel (2022)[5], the banking industry heavily depends on BDA for risk reduction, algorithmic trading, real-time fraud detection, and predictive analysis. In this context, Gartner (2020)[6] defines "BDA" as "a methodology with high volume, high velocity, and great variety that enhances insight discovery, decision-making, and process automation" in terms of data processing, enabling financial institutions to use data from a variety of sources, including transaction records, customer interactions, social media, and market trends (SBI, ICICI Bank, & PwC, 2022).

---

[1] Dr. Chandrakala Lavudya, M.Com, MBA (Finance & HRM), Ph.D. Faculty of Commerce, GDC Uppal, Hyd., Telangana.
[2] Project manager & Scrum Master at TCS, Hyd. & Academic Counsellor, Dr. B R Ambedkar Open University, Hyderabad.
[3] Kumar, S., & Sharma, A. (2023). The impact of Big Data on operational efficiency in Indian banks. International Review of Financial Studies, Vol. 22(5), pp: 210-228.
[4] Gupta V, Sharma P, & Mehta S. (2022). Big Data Adoption in Indian Banking Sector: Challenges and Opportunities. Journal of Business Analytics, Vol. 9(3), pp: 75-92.
[5] Choudhury R, & Patel M. (2022). Leveraging Big Data for Predictive Analytics in Financial Services: A Case of Indian Banks. International Journal of Banking Studies, Vol. 27(4), pp: 120-138.
[6] Gartner. (2020). Big Data Analytics: The evolving landscape of data-driven decision-making. Gartner Reports.

European Economic Letters
ISSN 2323-5233
Vol 15, Issue 1 (2025)
http://eelet.org.uk

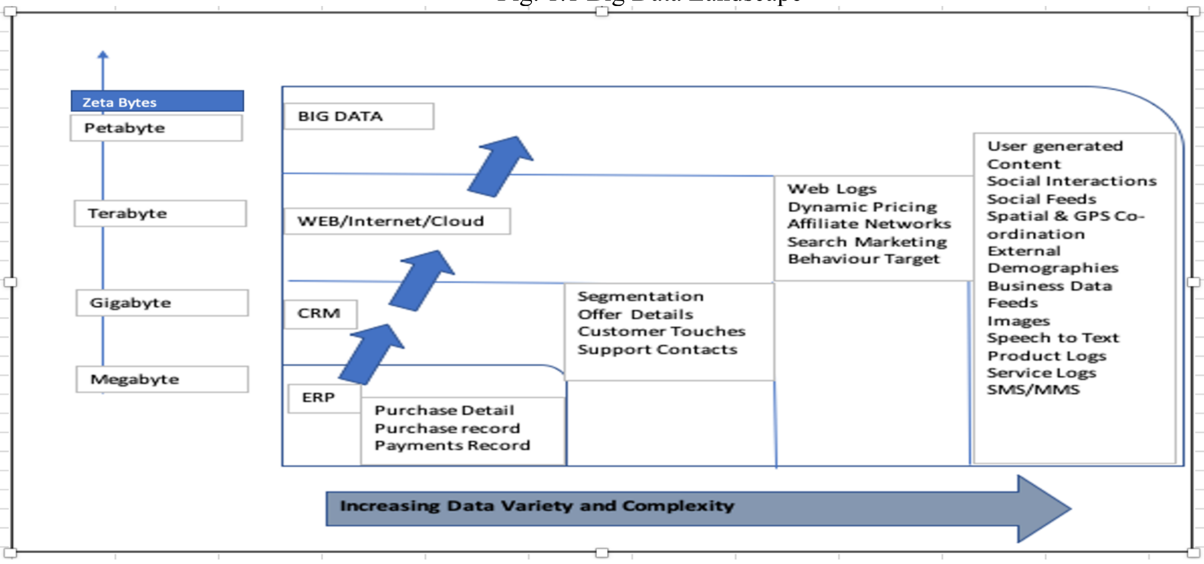
Gartner defines Big Data as a high-volume velocity, i.e., the speed at which the data is generated and a variety (various types) of information assets that are cost-effective, innovative forms of data processing for improved insights and better decision-making. 2.5 quintillion bytes of data are being generated on a daily basis. Data volume is increasing exponentially from (TB) terabytes to (PB) petabytes, (EB) exabytes and now (ZB) zettabytes. According to IBM, 80 per cent of data that is captured on a daily basis is in unstructured format, i.e., data right from sensors that are used to gather updates on the climatic conditions, posts that made on the social media platforms/sites, any digital pictures and or videos, purchase-related transactional records, and mobile GPS signals, to name a few. All of this unstructured data is big data. Big Data is an assortment of vast and complex data sets that become complex to process using in-hand DBMS tools or traditional data processing applications. Big Data is a significant amount of information gathered from multiple social media websites, questionnaires, and voluntary product sales. This data is kept in computer databases and evaluated using software designed to handle vast, complex volumes of data while reaching conclusions at an increasing rate or a rapid pace.

BDA is a comprehensive method of analysing enormous amounts of data to discover information like data relationships, associations, internal patterns, actual trends in the market, and preferences of consumers to assist businesses in making profound/informed decisions in the interest of business. It is a sort of advanced analytics involving composite applications that include significant parts like predictive models, statistical algorithms, and what-if analysis powered by analytics systems. Online platforms (social media, media publishing outlets, blogs, etc.), data acquired by user devices (computers, mobile gadgets), corporate assets (archives, databases, etc.), and search inputs are a few key sources.

Big Data Analytics – Background, Evolution

The efforts to reduce the risks in banking transactions and increase reach to tap into a broader customer base need access to a considerable quantum of data and the capability to process this data to draw meaningful inferences that may be considered in decision-making. This is where BDA is poised to play a vital and imminent role in promoting the banking sector's growth and mitigating the quantum of risks, an endeavour to understand how BDA can be used effectively in the financial industry to formulate strategies to contribute to the growth of top and the bottom-line of the banking entities.

Fig. 1.1 Big Data Landscape



Source: Developed by Authors from Multiple Sources of BDA Evolution

Mobile devices, sensors, social media, scientific instruments and networks mainly generate Big Data. The payoff from using BDA for analysing transactions related to banking is enormous. The quantum of successful case studies continues to build, reinforcing broader research suggesting that when a firm injects data and analytics deeply into its banking operations, it can deliver effective sales and higher profit gains. The new strategy of data-driven sales, in-depth data on consumer behaviour, better predictions, and shorter decision-making cycles make companies adopt it faster. Big Data drives $232 billion in IT spending through 2016. With the advent of the internet, smartphones, and any other applications, digital data escalated. As per the NSA-National Security Agency, the internet processes enormous amounts of data daily, 1,826 petabytes (PB). In 2018, data generated daily amounted to 2.5 (TB) trillion bytes. Hitherto, the International Data Corporation (IDC) estimated that the data generated would double every two years. However, 90% of data was generated globally in the past two years. Google currently processes each second of over 40,000 searches, or 3.5 billion searches a day. Facebook users upload 300 million images, 510,000 comments, and 293,000 status updates daily. With all these figures at hand, a humongous amount of data is generated daily. Hence, a requirement to strategic plan on how banks can leverage data, analytics, frontline tools, and people to create business value. The plan's effectiveness shall lie in developing a common language, allowing management, technical professionals, data analysts/scientists, and marketing managers to discuss how significant outstanding returns come from.

Big Data Analytics Working Process

Analytics programs examine data sets to extract information and forecast results. However, several applications must first store, organize, and clean the data in an integrated, step-by-step preparation procedure before it can be examined appropriately.

1. **Data Collection**: Data is collated through various sources (banks, UPIs, wallets, transaction types, places, i-banking, m-banking, WhatsApp banking, etc.) in structured, semi-structured and unstructured forms across web, applications, mobiles and cloud, stored in repositories like a data lake/data warehouse. It can be processed depending on the expected output and the tool used. Hadoop is one of the tools, NoSQL (MangoDB, Apache CouchDB, Azure Cosmos DB, etc.)
2. **Data Process**: The stored data is processed, post data verification, data sorting, and data filtering, for further usage to improve the queries and enhance performance. (Apache Spark performs batch processing and real-time data stream processing).
3. **Data Scrub**: Processed data is scrubbed further for data redundancies, duplicity, elimination of invalid/incomplete fields, and entry into the correct format after data cleaning and correction.
4. **Data Analyse**: The structured data can now be analysed through the usage of various tools and technologies like data mining, predictive analytics, ML, and other statistical tool that can define and predict the outcomes of the data and make use of it for strategic decision-making or to understand trends or patterns for future purpose.

Application of BDA in Banking: Banks mainly use BDA for Marketing Analytics, Risk and Fraud Management, and Strategy Formulation. BDA helps banks segment customers, retain customers, manage campaigns, cross-sell, and up-sell. In risk and fraud analytics, banks use credit scorecards to estimate the propensity to default and build an early warning system (EWS) to get alerts on fraudulent practices. Banks use data visualization interfaces and profit and loss (P&L) reporting for strategy formulation. Banks like HDFC and ICICI invested in BDA technology since 2004 by building data warehouses and investing in cutting-edge data mining tools that unravel business trends, map customer preferences, and provide alerts to prevent risky occurrences. Accrued benefits motivate other bankers to create a system to capture and analyze big data. Public sector bank SBI also adopted BDA with IBM.

The significance of metrics for financial institutes like SBI and ICICI.

As financial companies undergo a digital transition, processing and analysing massive amounts of data becomes more critical. To increase their efficiency, the two largest banks in India, SBI and ICICI Bank, invest in cloud computing and implement automated learning and artificial intelligence (AI) based analysis models (EY, 2023). However, significant personnel challenges remain: retaining current employees, fostering resistance to change, and improving current competencies (Deloitte, 2022).

BIG DATA Functions in Financial Institutions

Big Data functions in the financial sector include numerous fields for assessing a 360-degree, ranging from capturing essential functions to complex lending commercial activities, functions like:

Table 1.1 Functions of Big Data Analytics in Financial Institutions

Employee Engagement	Operation Optimization and Real-time Offers Management
Customer Experience	Fraud Detection: Dodd-Frank & Basel Regulation-2008 Recession
Loss Forecasting, Churn Analytics	Compliance and Regulatory: KYC & AML
API-based Early Warning system	Customer Segmentation: Depending upon the needs
Predicting Customers' Lifetime Value	Personalized Marketing: To cater to future needs
Recommendation Engines	Risk Management: Market Risk, Liquidity Risk, etc.
Product Mix Analysis	Channel Optimization, Rule-based
Customer Segmentation	Predictive Analytics-based Anti-Fraud System
Spend, Lead Funnel Analysis, Social Media Analytics, Cross or Up-sale Analytics.	

The three V's of Big Data (Volume, Velocity, and Variety) impacted the financial sector, mainly banking at various junctures with time and growing more extensive customer base and their individual requirements, especially in investment banking (Wealth Management), Velocity and Volume are key prime factors. Various big data technologies, such as cloud computing or Hadoop, have pioneered to tackle and cater to the vast amount of data generated. Initially, financial intermediaries were reluctant to use such technologies but needs gradually evolved in the economic segment, especially in banks.

Characteristics of Big Data (3 Key Parameters and 2 Outcomes of BD)

Volume: With the advent of internet-based apps, user numbers scaled up exponentially across geographies at various time zones, leading to the apparent generation of extensive data

Variety: Text, Voice, Social networking, Video, Hyper-Media data

Velocity: Batch processing often takes 2-12 hours, and analysing this was a considerable time lag. To harness this available data in real-time, Big Data's need was mandatory,

Veracity: To derive a meaning from the processing of the Big Data,

Value: To distinguish data in terms of value.

The subsequent data processing capacity does not scale up linearly with the resource. Vertical scaling does not help extensive data, thus, Big Data's evolution. Banks started using BDA in their operations in various fields like marketing, collections, risk management (credit policy, risk modelling or segmentation), operations, regulatory norms, human resources optimization, reporting, and governance.

Advanced Analytical Solutions

The table below depicts the analytical solutions across various industry types like Consumer Finance, Consumer Goods and Retail, Manufacturing and Supply Chain, along with the business focus areas and various Big Data tools and techniques that can be used.

Table 1.2 Analytical Solutions

Industry	Business Focus	Tools and Techniques
Consumer Finance		SAS, SPSS, R, VBA
Credit Cards	Investment Optimisation	Cluster Analysis
Loans & Mortgages	Revenue Maximisation	Factor Analysis
Retail Banking & Insurance	Cost & Process Efficiencies	Structural Equation Model
Wealth Management	Forecasting	Conjoint Analysis
Consumer Goods and Retail	Predictive Modelling	Perceptual Analysis
CPG & Retail, Consumer Durables	Risk Management	Neural Networks
Manufacturing & Supply Chain	Pricing Optimisation	Chaid or CART
High Technology OEMs	Customer Segmentation	Genetic Algorithms
Automotive	Drivers Analysis	Support Vector Machines
Logistics & Distribution	Supply Chain Management	Sentiment Analysis

Source: Compiled from Multiple Bank Websites

BDA help banks in areas like branch-layout planning, banking products assortment (merchandising materials), vendor management that constitutes CMS, bank maintenance, inventory, and sales forecast. It also helps in market analysis, market mix models, liabilities pricing, loyalty analytics, store operations like workforce analysis, fraud detection and loss prevention, and category sales reporting and analysis. Strategical planning helps introduce new products and track the overall performance of banks or branches and workforce, along with customer clustering and key value analysis.

Review of Literature

Big data analytics (BDA) has become a transforming instrument in banking operations, greatly enhancing efficiency, risk management, and customer service. **Jaspreet Singh et al. (2022)** underlined that BDA helps banks to have a more customer-centric stance, thereby enhancing customer retention and service efficiency and handling hazards related to online transactions. Similarly, **Bansal et al. (2022)** underlined the data-intensive character of the banking industry and the need for BDA to examine large data sets to reveal decision-making patterns, consumer insights, and market trends. Phan and Tran (2022) suggested a conceptual framework for BDA in banking, showing how it improves operational efficiency, risk management, and strategic decision-making. They underlined the significance of robust technology infrastructure and administrative backing for effective execution. **Ravinder (2021)** investigated BDA's function in financial services and claimed it improves marketing power, fraud detection, compliance monitoring, and non-performing asset (NPA) tracking, facilitating quicker and more knowledgeable decision-making. **More and Moily (2021)** underlined this viewpoint: BDA enables banks to examine extensive, varied data sets to find concealed trends and maximise corporate plans. By combining digital infrastructure with financial services, providing predictive analytics for decision-making, and tackling regulatory issues, **Khatri et al. (2021)** explored how BDA propels fintech advances. By using unstructured data from online transactions and ATMs, BDA helps risk management and consumer segmentation, hence improving fraud detection and regulatory compliance, according to **Shakya and Smys (2021)**.

Furthermore, **Hasan et al. (2021)** looked at how data innovation affects banking operations and found that, although needing cautious deployment to reduce security issues, BDA changes financial decision-making, increases profitability, and improves operational security. BDA became a key element in bank operations, optimising efficiency, customer service, and financial performance while managing related risks.

Statement of Problem

Though its influence on efficiency, risk assessment, fraud detection, client segmentation, and service delivery are underexplored, BDA in banking has changed operations. Leading financial companies like the State Bank of India (SBI) and ICICI Bank use BDA to simplify procedures, cut costs, and enhance decision-making. Its adoption, therefore, is more or less effective depending on the technical infrastructure and the flexibility of banking staff members. Evaluating the actual performance of BDA requires knowledge of how it improves operational efficiency while handling fraud concerns, maximising consumer support, and supporting cost reductions. Apart from operational advantages, BDA enables banks to create customised financial products, forecast market trends, and make data-driven choices, enabling competition. Still, issues like integration complexity and worker preparation exist. Focusing on its influence on banking efficiency and staff adaptability, this paper intends to assess BDA's function in banking operations to provide ideas for future optimisation.

Objectives

The study's objective is framed in line with the banking personnel’s adoption of BDA technology, which is associated with the perspectives of SBI and ICICI banks.

1. To explore the relationship of adopting Big Data Analytics technology in SBI and ICICI banks and its impact on banking operations by banking personnel.

Research Methodology

This study employs quantitative and statistical methods to examine the impact of BDA technology adoption on the operational and staff efficiency of SBI and ICICI banks. It utilizes structured statistical analysis to investigate its impact on banking operations, decision-making, and human roles in the sector.

- A stratified random sample of 418 bank personnel of SBI and ICICI Banks ensures representativeness. Banking risk management, fraud detection, client service, and data analytics are integrated. The study investigates BDA effects adoption within SBI and ICICI.
- A conventional, closed-ended, Likert-scale questionnaire was collected for the primary data on bank personnel's adoption of BDA technology and associated merits and issues. Secondary data was obtained

European Economic Letters
ISSN 2323-5233
Vol 15, Issue 1 (2025)
http://eelet.org.uk

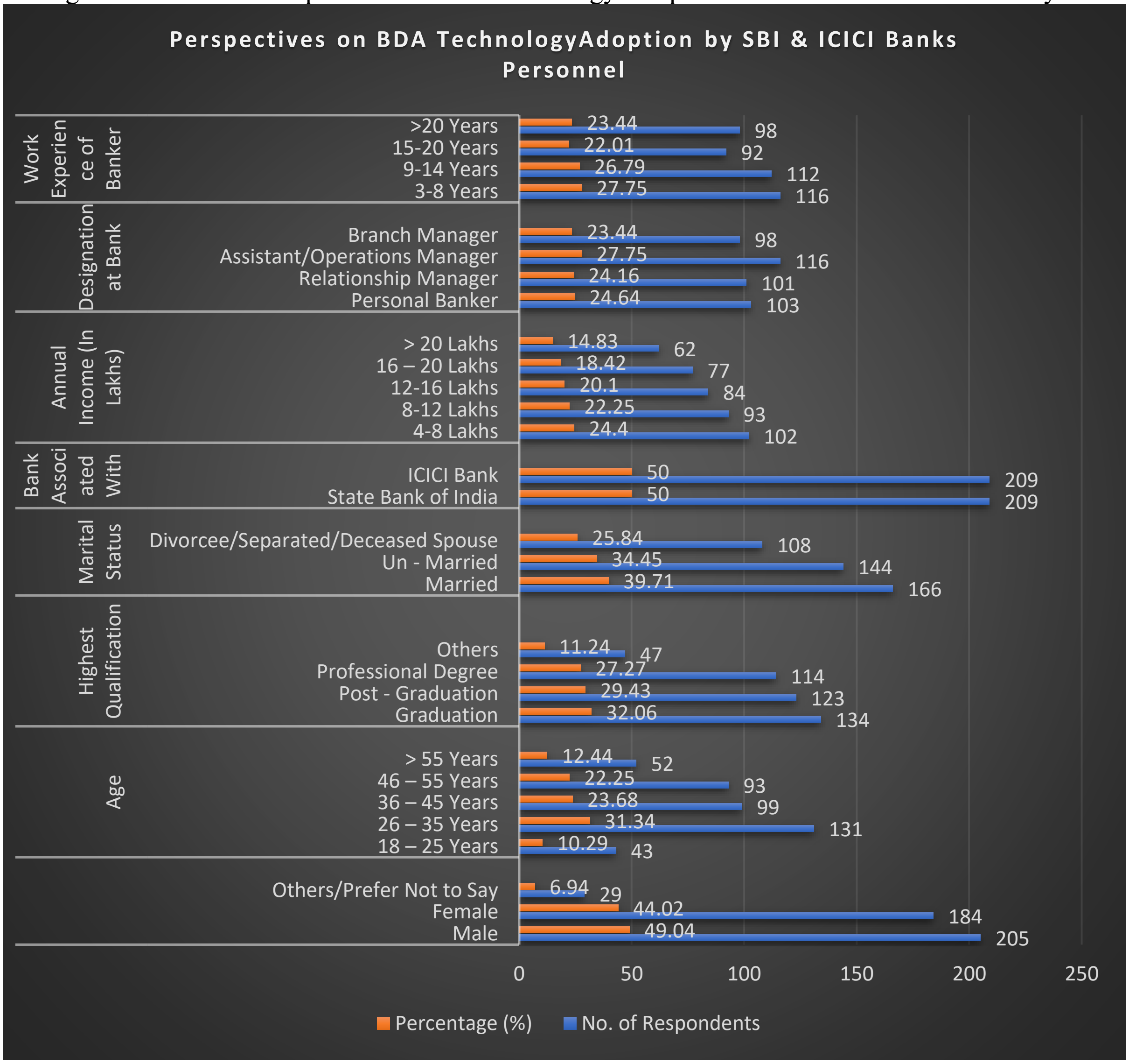
from bank reports, regulatory documents, financial statements, and BDA banking literature. Comparative analyses and industry trends enhanced the study.

- The questionnaire's reliability and validity were evaluated for internal consistency using Cronbach's Alpha. Scores exceeding 0.7 signify reliability. Determining sample size for factor analysis is conducted through KMO and Bartlett's Test.
- Data analysis utilised both descriptive and inferential statistics. The patterns of BDA were illustrated through the mean, standard deviation, and frequency analysis. The impact of BDA was illustrated through factor analysis, employing communalities, explaining total variance, and utilizing component and rotated component matrices to classify analogous components.
- Inferential analysis investigates the effects of BDA through a correlation matrix. t-tests and ANOVA will assess employees' perspectives and job functions at SBI and ICICI banks. The Chi-Square test will determine if the deployment of BDA influences bank efficiency.

Findings and Symposium

These responses show banks' adoption of the Big Data Analytics (BDA) technology and its impact on the demographics of bank staff.

Fig. 1.2 Bank Staff Perspective on BDA Technology Adoption in SBI & ICICI Banks: Analysis



Source: Primary Data Analysis

European Economic Letters
ISSN 2323-5233
Vol 15, Issue 1 (2025)
http://eelet.org.uk

The study distribution by age shows that 27.75% of respondents have 3-8 years of experience, while 23.44% have over 20 years of experience. Assistant/Operations managers comprised 27.75%, followed by Personal Bankers, which comprised 24.64%. Regarding annual income distribution, about 24.4% of respondents earn between 4 and 8 lakhs, and 14.83 % earn over 20 lakhs. The equal involvement of ICICI Bank and State Bank of India (50% each) ensures institutional perspective. Married staff make up 39.71%, and single were 34.45%. Academic studies show that most respondents were graduates (32.06%) or postgraduates (29.43%), while just 11.24 per cent fell into the "Others". Most responders were 26–35 years old (31.34%), followed by 36–45 years (23.68%). The gender distribution is nearly equal: 49.04% men and 44.02% women. These perspectives provide a fundamental understanding of the personnel dynamics that affect BDA adoption in the banking sector's operations.

BDA Expertise and Impact on Bank Operations – Key Factors & Descriptive Statistics

The key factors of SBI and ICICI banks personnel's BDA adoption and its impact on the operations are

- **Impact of BDA on Bank Operations Increases Efficiency**: Evaluates how much bank personnel believe BDA improved operational efficiency and staff believes that efficiency improved with a Mean of 4.20, with moderate S.D (0.857) indicating respondents' opinions are generally consistent, if not unanimous. A higher ranking denotes an improvement in operational effectiveness.
- **Impact of BDA on Accuracy and Effectiveness on Risk Assessment**: It evaluates the effects of BDA on the precision and efficiency of the bank's risk assessment procedures and offers perceptions on how BDA might enhance it. The high mean (4.42) shows a favourable impression of BDA's effect on risk assessment processes, and a high degree of agreement is indicated by the low S.D (0.719).
- **Impact of BDA to detect/identify Fraudulent Activities & Prevention**: Employees consistently have a reasonable opinion of BDA's contribution to fraud detection and prevention, as evidenced by a high mean of 4.28 and a low S.D (0.704).
- **Impact on Customer Segmentation and Target Market**: It investigates how BDA affects marketing campaign targeting and client segmentation and aids in evaluating BDA's performance in tailored marketing tactics and observed an S.D of 0.892, which indicates some response variability, and the mean (4.21) points to a favourable impact on these two areas.
- **Impact of BDA Optimisation on Customer Support and Service Delivery**: BDA's streamlined customer service and assistance sheds light on BDA's contribution to optimal customer service with a Mean of 4.25, moderate S.D (0.794), signifying considerable variation in viewpoints.
- **Impact of BDA contribution for Cost savings**: It assesses how much BDA contributed to operational cost reductions for the bank. The mean (4.01) shows that people's opinions on BDA's cost-savings contribution are generally favourable. Nevertheless, the more significant S.D (1.024) indicates a greater diversity of viewpoints among the bank staff.
- **Impact on Data-Driven and Informed Decisions**: BDA is perceived as data-driven for informed decisions with an observed Mean of 4.17 and moderate S.D (0.831), a generally favourable view.
- **Impact of BDA in Predict/Anticipate Market Trends/Customer Behaviour:** BDA perceived to anticipate or predict the market trends on customer behaviour with a Mean of 3.87 are generally favoured backed by a moderate S.D of 0.896 respondents' opinions differ.
- **Impact of BDA on Development & Tailoring Financial Products/Services:** BDA's impact on customised financial products/services were efficient, with a mean of 4.11 and moderate S.D of 0.875, indicating a range of opinions.
- **Impact of BDA on Banks in Harnessing Competitive Advantage:** BDAs implementation harnessed competitive spirit with an observed mean of 3.95, and higher significance S.D (0.927) perspectives are not all the same view among banking personnel's preserving a competitive edge.

Descriptive data shows that human personnel's impressions of BDA's influence on banking operations are generally good, notwithstanding differences in agreement and viewpoints.

Staff's Impact on Bank Operations of BDA Using Correlation Matrix

A correlation matrix helps determine the direction and degree of correlations between variables in statistical analysis and is used for analytical approaches, including principal components and regression.

European Economic Letters
ISSN 2323-5233
Vol 15, Issue 1 (2025)
http://eelet.org.uk

A thorough correlation matrix illustrated the interactions between several elements connected to the influence of BDA on banking operations. Each aspect, from enhancing productivity to preserving competitive advantage, is associated with other elements that reveal trends in staff's opinions. The correlation values demonstrate complex interactions between different aspects, ranging from weak to moderate positive correlations.

Table 1.3 Impact on Bank Operations of BDA - using Correlation Matrix[a]

Correlation	BIBO1	BIBO2	BIBO3	BIBO4	BIBO5	BIBO6	BIBO7	BIBO8	BIBO9	BIBO10
BIBO1	1.000									
BIBO2	.149	1.000								
BIBO3	.264	.173	1.000							
BIBO4	.267	.279	.164	1.000						
BIBO5	.222	.036	.365	.184	1.000					
BIBO6	.213	.267	.092	.478	.206	1.000				
BIBO7	.179	.047	.013	.101	.153	.139	1.000			
BIBO8	.100	.031	.068	.129	.061	.279	.346	1.000		
BIBO9	.179	.117	.023	.170	.067	.116	.377	.248	1.000	
BIBO10	.217	.219	.145	.351	.211	.304	.172	.316	.225	1.000

a. Determinant = 0.223 BIBO=Banking Impact on Banking Operations

Interestingly, elements like fraud protection and detection, client targeting and segmentation, and customer assistance optimisation show somewhat positive correlations, indicating that staff members believe these elements are related. Furthermore, a considerable degree of multicollinearity among the variables is indicated by the determinant value of 0.223, suggesting that specific components may share shared variance. Essentially, this correlation matrix serves as a basis for additional analysis and strategic decision-making by offering insightful information on the consistent or inconsistent viewpoints on how BDA affects different aspects of banking operations.

Impact on Bank Ops of BDA-Cronbach's Alpha & Kaiser-Meyer-Olkin (KMO) & Bartlett's Test

The reliability statistics for components linked to banking staff's know-how of BDA and its impact on banking operations, Cronbach's Alpha, is used to evaluate the internal consistency/reliability of a group of scale/test items observed dependability of 0.704, indicates stronger dependability, i.e., they measure the same underlying construct, thus increases study validity as a tool to determine how well-informed personnel on BDA are in the sector.

KMO & B is a statistical tool for determining if data are suitable and aids researchers in deciding if the data are suitable for factor analysis to find underlying correlations between variables. The KMO test results vary from 0 to 1; larger values suggest more incredible eligibility for factor analysis is appropriate for the variables in the dataset as they are likely to have a common variance.

Table 1.4 Staff's Impact on Bank Operations of BDA using KMO and Bartlett's Test

Cronbach's Alpha Value	10 Factors or Items	0.704
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.707
Bartlett's Test of Sphericity	Approximate (~) Chi-Square	621.938
	df (degree of freedom)	45
	Sig. (Significance value)	0.000

The table presents the KMO Measure of Sampling Adequacy and B Test of Sphericity results to measure the adequacy sample for factor analysis, and KMO=0.707 is considered good, suggesting data suitable for factor analysis. Bartlett's Test of Sphericity assesses if the correlation matrix is an identity matrix, indicating no relationships between the variables. The approximate chi-square value is 621.938, at a 0.000 significance level (Bartlett's Test <0.05), which implies variables for the factor analysis. A low p-value (<0.05) indicates that the correlation matrix is not an identity matrix, providing evidence that the relationships exist between the variables, indicating underlying patterns and relationships among the variables.

Staff's Impact on Bank Operations of BDA - Using Communalities

In the component analysis framework, communality is the % of the variation in an observable variable that the common factors can explain. Each variable's total variation is divided into two categories throughout the component analysis process. While unique variation is specific to each variable and cannot be explained by the factors, common variance is shared with other variables. It is taken into account by the underlying factors. Communalities are usually stated as values in the 0 to 1 range; 1 denotes that all variation is unique and has no common variance with other variables, and 0 implies that all variance is shared. Communalities are frequently included for each variable in the outcome of factor analyses, offering information on how well the factors explain the observed variance in each variable. Greater communalities point to a better fit to the factor model by suggesting that standard components explain a more significant percentage of the variance in the variable.

Table 1.5 Staff's Impact on Bank Operations of BDA - using Communalities

Description	**Initial**	**Extraction**
Impact of BDA on Bank Operations- Efficiency	1.000	0.385
Impact of BDA on Accuracy and Effectiveness on Risk Assessment	1.000	0.439
Impact on BDA to detect and identify Fraudulent Activities	1.000	0.642
Impact on Customer Segmentation and Target Market	1.000	0.608
Impact of BDA Optimisation on Customer Support and Service Delivery	1.000	0.609
Impact of BDA Contribution for Cost Savings	1.000	0.574
Impact of BDA on Banks to Make Data-Driven and Informed Judgements	1.000	0.634
Impact of BDA to Predict/Anticipate Market Trends and Customer Behaviour	1.000	0.499
Impact of BDA on Development & Tailoring Financial Products or Services	1.000	0.489
Impact of BDA on Banks in Harnessing Competitive Advantage	1.000	0.436

Extraction Method: PCA

Communalities are needed to determine BDA's effect on banking operations. The percentage of each variable's variation that may be accounted for by common variables found throughout the investigation is represented by a community. All variables have a communality of 1.000 at first, implying they share a common variance with other variables. Commonalities decrease following the PCA extraction procedure, indicating that the retrieved components explain not all variation in each variable. The extraction communalities show the percentage of variation maintained following factor extraction, varying from 0.385 to 0.642. Greater communalities sometimes indicate a greater extent to which the extracted common factors account for variance in original variables. Communalities provide insights into shared variation across variables in the context of their influence on banking operations. They show how well-selected variables fit with components identified during analysis.

Staff's Impact on Bank Operations of BDA - Total Variance Explained

The cumulative variability in observed variables explained by factors found in factor analysis is the total variance explained, denoted by % of the overall variation in initial variables explained by shared components identified during analysis. Finding underlying latent factors contributing to observed variance in a set of variables is the goal of factor analysis. Essential indicator for assessing how effectively discovered variables capture and explain variability in the dataset. The common way to quantify as % is to show what % of the overall variation in original variables is captured by extracted components. More significant percentages indicate more effective factor analysis and imply a greater proportion of the dataset's variability explained by found factors. The retrieved components concerning BDA's effect on banking operations explain total variation. Each row corresponds to a distinct element.

Table 1.6 Staff's Impact on Banking Operations towards BDA using Total Variance Explained

C	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cum. %	Total	% of Variance	Cum. %	Total	% of Variance	Cum. %
1	2.746	27.465	27.465	2.746	27.465	27.465	1.928	19.284	19.284
2	1.402	14.019	41.484	1.402	14.019	41.484	1.791	17.907	37.191
3	1.167	11.666	53.150	1.167	11.666	53.150	1.596	15.959	53.150
4	.911	9.113	62.263						
5	.794	7.939	70.202						
6	.725	7.251	77.452						

7	.701	7.008	84.460						
8	.609	6.095	90.555						
9	.525	5.246	95.801						
10	.420	4.199	100.000						

Extraction Method: PCA Cum. % = Cumulative %, C=Component

Initial Eigenvalues: Before any extraction/rotation, they show variation in original variables. Initial eigenvalues add up to 2.746; each component accounts for a portion of the overall variance. Original data had intrinsic variability, as indicated by the first eigenvalues.
Extraction Sums of Squared Loadings: Post Principal Component Analysis, the extraction procedure finds common components representing shared variation across the variables. The squared loading extraction sums show how much variation is explained by each component.
Rotation Sums of Squared Loadings: A rotation may occasionally be performed to improve components' interpretability. The variation that remains after the rotation sums of squared loadings show rotation. Kaiser normalisation is used in this Varimax rotation. The first three components account for 53.15% of the variation. This implies that these three components capture a substantial amount of the data. Achieving a balance between minimising needless complexity and keeping just the correct number of components to identify significant patterns in the data is crucial. Given their considerable contribution to the cumulative variance, the first three components may be kept in place, depending on the particular objectives of the study and the required amount of explained variation.

Staff's Impact on Bank Ops of BDA - Using Component Matrix[a] & Rotated Component Matrix[a1]
Component Matrix: The table shows how each variable is loaded onto retrieved components in the PCA. It offers a valuable perspective on the connections between original variables and extracted components, facilitating the interpretation and utilisation of PCA findings. PCA was used to extract the factor "Impact on Banking Operations" and the resultant rotated component matrix. Values represent each variable's loadings.
Rotated Component Matrix The factor "Impact on Banking Operations," extracted using Principal Component Analysis with Varimax rotation, as a rotated component matrix. After rotation, the values in the matrix show how each variable (item) is loaded onto indicated components.

- Component 1: High positive loading variables include the Impact of BDA on Bank Operations (factor 1), Impact on customer Segmentation/Target Market (Factor 4), Impact of BDA contribution to Cost Saving (Factor 6), and Impact of BDA on Bank in Harnessing Competitive Advantage (Factor 10), variables positively correlate with Component 1 indicates that they substantially contribute to it.
  - The impact of BDA on the Accuracy and Effectiveness of Risk Assessment is one variable with a strongly favourable loading. Component 1 positively correlates with the Impact of BDA on the Accuracy and Effectiveness of Risk Assessment.
- Component 2: High positive loading variables were observed in the impact of BDA optimisation on customer support and service delivery (Factor 5) with a positive correlation. High negative loading variables on Impact on BDA to detect and identify Fraudulent Activities (Factor 3).
  - Impact on Customer Segmentation and Target Market, bank impact bank operator 6, bank impact bank operator 8, and bank impact bank operator 9 are variables with substantial positive loadings. Component 2 and these factors have a positive correlation.

Table 1.7 BDA Impact on Bank Operations using Component Matrix[a] & Rotated Component Matrix[a1]

Factors	Component			Rotated Component		
	1	2	3	1	2	3
Impact of BDA on Bank Operations- Efficiency	.534					0.533
Impact of BDA on Accuracy and Effectiveness on Risk Assessment				0.657		
Impact on BDA to detect and identify Fraudulent Activities		-.511				0.790
Impact on Customer Segmentation and Target Market	.648			0.756		
Impact of BDA Optimisation on Customer Support and Service Delivery			.535			0.773
Impact of BDA Contribution for Cost Savings	.640			0.731		
Impact of BDA on Banks to Make Data-Driven and Informed Judgements		.582			0.785	

Impact of BDA to Predict/Anticipate Market Trends & Customer Behaviour		.505			0.683	
Impact of BDA on Development and Tailoring Financial Products/Services		.512			0.691	
Impact of BDA on Banks in Harnessing Competitive Advantage	.644			0.522		

Component Matrix: Extraction Method: PCA a. three components extracted
Rotated Component Matrix: Extraction: PCA Rotation Method: Varimax with Kaiser Normalization a1. Rotation converged in 5 iterations

- Component 3: It has a negative correlation with this variable. Components 2 and 3 capture specific characteristics linked to positive and negative effects, respectively, whereas Component 1 represents factors connected to the overall favourable influence on banking operations.
    - The impact of BDA in detecting and identifying Fraudulent Activities, the Impact of BDA Optimisation on Customer Support and Service Delivery, and the Impact of BDA on banks to make Data-Driven and Informed Judgements are variables with significant positive loadings. Component 3 and these factors have a positive relationship.

Rotated Component Matrix: The varimax rotation approach simplifies component interpretation by optimising the variance of loadings inside each component and concurrently maximising differences between loadings. Loading in a rotated component matrix seems more focused, facilitating the understanding of forces influencing each component. Component 2 captures a different set of favourably correlated elements, Component 3 could reflect a different aspect of the effect, and Component 1 appears to indicate factors connected to the beneficial impact of BDA on banking operations. To better understand the fundamental causes and how they affect the perceived effect of BDA on banking operations, researchers should examine the specifics of each variable.

Summary of Hypotheses Tests and Results

The table presents statistical tests performed on different demographic variables to understand their impact on a dependent variable (presumably satisfaction/ perception). Various statistical investigations, like t-test, ANOVA, and Chi-Square test, were applied based on their nature. The significance of differences among groups is determined using p-values, with a standard threshold of 0.05 significance.

Table 1.8 Summary of Hypotheses

Variable	Statistical Test Used	Mean Score	Significance (p-value)	Null Hypothesis Result	Impact
Gender	t-Test	4.13 – 4.16	0.000	Rejected	Significant Impact
Age	ANOVA	4.06 – 4.22	0.150	Accepted	No Significant Impact
Qualification	Chi-Square	4.11 – 4.23	0.970	Accepted	No Significant Impact
Marital Status	Chi-Square	4.14 – 4.16	0.000	Rejected	Significant Impact
Annual Income	ANOVA	4.08 – 4.24	0.120	Accepted	No Significant Impact
Designation	Chi-Square	4.12 – 4.19	0.610	Accepted	No Significant Impact
Experience	ANOVA	4.08 – 4.23	0.140	Accepted	No Significant Impact

Gender (t-Test): Males, females, and other gender categories have similar mean values (~4.14–4.16). The t-statistic (189.52) and p-value (0.000) indicate a significant difference among gender groups. The null hypothesis is rejected, meaning gender plays a role in influencing the dependent variable.
Age (ANOVA Test): The mean scores range from 4.06 to 4.22, showing minor variations. The F-statistic (1.68) and p-value (0.150) suggest no significant difference among age groups. The null hypothesis is accepted, meaning age does not significantly impact the dependent variable.
Qualification (Chi-Square Test): Mean values are close, ranging from 4.11 to 4.23. The Chi-Square statistic (51.74) and p-value (0.970) indicate no significant difference. The null hypothesis is accepted, meaning educational qualification does not significantly impact the dependent variable.
Marital Status (Chi-Square Test): The mean values are almost identical (~4.14–4.16). The t-statistic (189.52) and p-value (0.000) indicate a significant difference. The null hypothesis is rejected, meaning marital status affects the dependent variable.
Annual Income (ANOVA Test): Mean values range between 4.08 and 4.24, showing minor differences. The F-statistic (1.87) and p-value (0.120) suggest no significant difference. The null hypothesis is accepted, meaning annual income does not significantly impact the dependent variable.

Designation (Chi-Square Test): Mean values slightly vary between 4.12 and 4.19. The Chi-Square statistic (91.25) and p-value (0.610) indicate no significant difference. The null hypothesis is accepted, meaning job designation does not significantly affect the dependent variable.
Work Experience (ANOVA Test): Mean values increase slightly with experience, from 4.08 to 4.23. The F-statistic (1.86) and p-value (0.140) indicate no significant difference. The null hypothesis is accepted, meaning work experience does not significantly impact the dependent variable.

Conclusion
Significant Factors: Gender and marital status significantly influence the dependent variable.
Non-Significant Factors: Age, qualification, income, designation, and work experience do not significantly impact the dependent variable.
Further, the observations suggest that personal demographics (gender, marital status) play a more considerable role in shaping perceptions or responses than professional factors (qualification, income, and experience). The results indicate that gender and marital status significantly influence the dependent variable, as evidenced by t-tests yielding statistically significant p-values (0.00). This suggests that these personal demographic attributes shape individual perceptions or experiences meaningfully. Conversely, variables such as age, educational qualification, annual income, job designation, and work experience exhibit no statistically significant impact, as demonstrated by non-significant F-statistics and p-values exceeding 0.05. These findings suggest that professional and economic attributes do not strongly differentiate perceptions within the studied population. The observed significance of gender and marital status necessitates a deeper examination of underlying factors contributing to this effect. Future research could explore sociocultural influences, workplace dynamics, and psychological factors that may mediate or moderate these relationships. Additionally, given that professional factors such as designation, income, and work experience do not exhibit a statistically significant impact, organizations might benefit from emphasizing workplace culture, engagement initiatives, and inclusion policies to foster a more universally positive experience across diverse employee demographics.

References
1. Accenture. (2021). The future of AI in banking: Overcoming resistance and driving adoption. Accenture Insights. https://www.accenture.com
2. Bansal, T., Sharma, P., & Singh, R. (2022). The impact of big data analytics on banking operations: A review. International Journal of Financial Studies, Vol. 10(2), pp: 45-62.
3. Bose, S., & Roy, A. (2023). Big Data Analytics in Banking: Transforming Financial Services through AI-driven Insights. Journal of Financial Technology, Vol. 18(2), pp: 45-61.
4. Choudhury, R., & Patel, M. (2022). Leveraging Big Data for Predictive Analytics in Financial Services: A Case of Indian Banks. International Journal of Banking Studies, Vol. 27(4), pp: 120-138.
5. Deloitte. (2022). The role of employees in digital banking transformation. Deloitte Insights.
6. EY (Ernst & Young). (2023). The digital banking revolution: How AI and Big Data shape financial services. EY Reports.
7. Gartner. (2020). BDA: The evolving landscape of data-driven decision-making. Gartner Reports.
8. Gupta, V., Sharma, P., & Mehta, S. (2022). Big Data Adoption in Indian Banking Sector: Challenges and Opportunities. Journal of Business Analytics, 9(3), 75-92.
9. Hasan, M., Rahman, T., & Chowdhury, A. (2021). Data innovation and banking transformation: The role of big data analytics. Journal of Banking & Financial Technology, Vol. 5(1), pp: 78-95.
10. Jaspreet Singh, K., Gupta, A., & Mehta, S. (2022). Enhancing banking efficiency and customer service using big data analytics. Journal of Financial Services Research, Vol. 15(3), pp: 120-135.
11. Khatri, R., Kumar, P., & Rajan, S. (2021). The role of big data in fintech innovations: Challenges and opportunities. Financial Technology & Innovations, Vol. 8(4), pp: 112-128.
12. Kumar, R. (2022). Skill Development in the Age of Big Data: Addressing the Gaps in Banking Workforce Training. Indian Journal of Finance and Economics, 15(1), 30-50.
13. Kumar, S., & Sharma, A. (2023). The impact of Big Data on operational efficiency in Indian banks. International Review of Financial Studies, 22(5), 210-228.
14. McKinsey & Company. (2021). Harnessing Big Data for Competitive Advantage in Financial Services. McKinsey Global Banking Report.

European Economic Letters
ISSN 2323-5233
Vol 15, Issue 1 (2025)
http://eelet.org.uk

15. PwC. (2022). Big Data and AI in Indian Banking: The Road Ahead. PwC Reports.
16. Reserve Bank of India (RBI). (2023). Data Security and Privacy Challenges in Indian Banking: A Regulatory Perspective. RBI Bulletin, Vol. 79(6), pp: 45-58.
17. More, S., & Moily, J. (2021). Uncovering market trends using big data analytics in the banking sector. International Journal of Business Analytics, Vol. 9(1), pp: 98-110.
18. Phan, T., & Tran, D. (2022). A conceptual framework for BDA in banking operations: Enhancing efficiency, risk management. Asian Journal of Business & Management, Vol.14(2), pp: 55-72.
19. Ravinder, K. (2021). The role of big data in financial services: Enhancing decision-making and risk management. Journal of Finance and Economics, Vol. 13(4), pp: 200-214.
20. Shakya, R., & Smys, S. (2021). Leveraging big data for risk management and customer segmentation in banks. Data Science & Financial Analytics Review, Vol. 7(3), pp: 87-102.