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Big Data Analytics Adoption in Financial Institutions

An Integrated Technology Acceptance Model (TAM) and Task–Technology Fit (TTF) Perspective

Janani S, Dr.S.Johnsi
Firebird Institute of Research in Management,
Coimbatore
janani.s@firebird.net.in, johnsi.s@firebird.ac.in

Abstract*—This research paper looks at the determinants of implementation of the Big Data Analytics (BDA) technology within the financial institution, especially focusing on the behaviour of employees with regards to their acceptance and use of the technology. Institutions are producing large amounts of structured and unstructured data in the modern digital financial landscape in the form of digital banking, mobile transactions, fintech systems and regulatory reporting systems. Though organizations are spending more to build analytics infrastructure, the inherent use of the systems largely rests on the perception of employees, complements of tasks, as well as dependability of the technology as opposed to the availability of technology. The research relies on the combination of Technology Acceptance Model (TAM) and Task Technology Fit (TTF) theory to establish the relationship between perceived usefulness, perceived ease of use, task technology, and technology characteristics and adoption of Big Data Analytics. Some of the primary data were gathered through a structured questionnaire and purposive sampling in the form of employees in the Indian financial institutions. A weighted response of 204 valid responses was analysed by applying descriptive statistics, reliability testing, correlation analysis, multiple regression methodologies in the SPSS software. The empirical results also show that employees tend to have positive perceptions of analytics systems as all independent variables have significantly positive causal links with Big Data Analytics adoption. The findings substantiate the claim that the adoption of analytics is a socio-technical process, which is influenced by all the three determinants of behavioural beliefs, job relevance, and technological robustness instead of one factor. Perceived usefulness was also one of the strongest predictors among them, ease of use, task alignment, and system reliability. The paper adds to the existing body of research on technology adoption through its empirical support to demonstrate an integrated TAM-TTF model in the financial institution setting. In practice, the results can be used to advise managers and policymakers to promote analytics adoption using user-friendly training, user-friendly system design, task-related personalization, and powerful technical support. Altogether, the study shows that effective implementation of Big Data Analytics needs not only sophisticated systems, but also the acceptance, operation compatibility, and organizational support of the employees.

Keywords*—*Big Data Analytics; Technology Acceptance Model; Task–Technology Fit; Perceived Usefulness; Perceived Ease of Use; Technology Characteristics; Financial Institutions

I. INTRODUCTION

A. Introduction

Over the past years, the financial institutions have been functioning with an environment that is ever more digitalized and driven with data and information in decision-making. The rapid expansion of digital banking platforms, electronic payment systems, mobile applications, and fintech services has increased both the volume and sophistication of data produced in the financial industry. Data processing and reporting tools which were traditionally used are unable to process such large volumes of data nor can they extract any meaningful insights on a timely basis. Thus, Big Data Analytics (BDA) has become a significant instrument that financial institutions should explore to improve the quality of decisions, operational performance and risk management.

Big Data Analytics allows companies to process vast amounts of structured and unstructured data to determine trends, patterns, and relationships that may be used to make more informed decisions. Within the financial sector, analytics is very commonly used in fraud detection, credit risk assessment, customer behaviour analysis, regulatory compliance, and performance measurement. The development of real-time payment systems, financial inclusion programs, and digital lending services in India has made analytics in financial institutions even more relevant.

Even with considerable investments made in analytics infrastructure, financial institutions do not make the most out of Big Data Analytics. Practically, employees tend to underuse or irregularly use analytics systems. The success of analytics programs relates not only to the technological presence but to the perception of employees towards analytics systems that promise convenience, usability, and relevance to their tasks. It is against this realization that the current study investigates the factors that impact the adoption of Big Data Analytics in financial institutions, with particular focus on individual-level behaviour in adoption.

B. Background of the Study

The financial institutions in the world are one of the most data-intensive organisations. Each transaction, contact with customers, and every compliance report or risk evaluation results in data that needs to be processed and analyzed in order to serve organizational goals. The improvement of Big Data technologies has provided financial institutions with new prospects to boost efficiency, accuracy, and strategic decision-making due to the ability to gather, store, and analyze large volumes of data.

The Indian financial sector is where this transformation has been especially fast, with a sharp rise in digital transactions achieved through digital banking, the Unified Payments Interface (UPI), mobile wallets, and fintech platforms. Regulatory and industry reports indicate that Indian financial institutions record billions of transactions each year, generating complex datasets that cannot be well managed and regulated without sophisticated analytical skills (Reserve Bank of India [RBI], 2024).

Big Data Analytics holds great importance in resolving some of the major problems financial institutions are confronted with, such as fraud, credit risk, customer segmentation, and regulatory compliance. Systems based on analytics also allow real-time monitoring, predictive modelling, and early warning systems, which are quite important in an industry with high financial risk and tough regulatory demands.

Nonetheless, the presence of sophisticated analytics systems does not necessarily guarantee successful implementation. Common problems that many financial institutions still encounter include resistance from employees, insufficient analytical skills, perceived system complexity, and poor correlation between analytics tools and work tasks. Employees can rely on their experience or intuition instead of analytics-informed insights, which inhibits the value of analytic investments.

Recent studies point to Big Data Analytics as a socio-technical process, the use of which depends on social, task, and technological aspects of behaviour patterns (Dwivedi et al., 2024). Perceived usefulness, perceived ease of use, task-technology fit, and technology characteristics are all perceived constructs that have been found to be important determinants of adoption. Understanding the effects of these factors on adopting analytics in Indian financial institutions forms the basis of the current study.

C. Research Problem

Despite the fact that Big Data Analytics is starting to attract growing interest in scholarly literature and industry practice, there are still a number of significant gaps that remain to be addressed, especially when it comes to financial institutions. A significant portion of the literature presently used is on the organizational-level outcomes, such as financial gain, efficiency and competitive edge. Although these studies discuss the strategic importance of analytics, they usually neglect the place of individuals who are the primary users of analytics systems.

Analytics platforms have been introduced at most financial institutions, but they are not considered a significant part of everyday work processes among employees. Lack of trust, perceived complexity, and inadequate fit to job requirements may make employees reluctant to use the results of analytics. This discrepancy between the presence of analytics and their practical implementation raises questions about the efficiency of analytics efforts.

The issue is particularly acute within the Indian financial sector, as institutions work under strong regulatory frameworks, legacy systems, and a multifaceted workforce with different degrees of technology adequacy. Furthermore, previous research often studies technology adoption theories independently, either as user perceptions or as system-task fit outcomes. These isolated views have limited empirical studies that combine to achieve an overall understanding of Big Data Analytics adoption.

To this end, the main research problem addressed in this study is the insufficient empirical research on the variables that affect the use of Big Data Analytics at the individual level among financial institutions, especially in the Indian regulatory and operational context.

D. Research Questions and Objectives

Based on the research problem identified above, the study seeks to answer the following research questions:

1) How does perceived usefulness influence Big Data Analytics adoption in financial institutions?

2) What role does perceived ease of use play in employees' adoption of Big Data Analytics?

3) To what extent does task–technology fit affect Big Data Analytics adoption in financial institutions?

4) How do technology characteristics influence Big Data Analytics adoption among employees?

In line with the research questions, the objectives of the study are as follows:

1) To examine the influence of perceived usefulness on Big Data Analytics adoption in financial institutions.

2) To analyze the effect of perceived ease of use on Big Data Analytics adoption among employees.

3) To assess the impact of task–technology fit on Big Data Analytics adoption in financial institutions.

4) To evaluate the role of technology characteristics in influencing Big Data Analytics adoption.

5) To develop an integrated framework that explains Big Data Analytics adoption using behavioral, task-related, and technological perspectives.

E. Significance of the Study

This research means a lot to a number of stakeholders. Academically, it adds to the literature on technology adoption as it explicitly examines the individual-level adoption of Big Data Analytics in financial institutions. The study combines the Technology Acceptance Model with elements of the Task-Technology Fit model to give more detailed support to analytics adoption behaviour.

To managers and practitioners working in financial institutions, the findings provide useful information on the issues driving or discouraging the use of analytics amongst employees. These lessons can be used to assist organizations to enhance system usability, develop effective training programs, and improve the alignment between analytics tools and job duties.

Politically and from a regulatory standpoint, especially in the Indian setting, the research identifies technological aspects such as data security, system reliability, and integration capability as critical considerations. Understanding these factors may facilitate the creation of more robust data governance and digital transformation policies. Unless these adoption challenges are addressed, financial institutions may continue to experience underutilization of analytics systems, poor decision-making, and risk management inefficiencies.

II. LITERATURE REVIEW

A. Overview

The international financial services industry is experiencing a whirlwind of change propelled by technology advancement, proliferation of data, and growing customer demands (RBI, 2024; McKinsey & Company, 2024). Big Data Analytics (BDA) has become a key strategic resource over the past few years, allowing financial institutions to leverage volumes of structured and unstructured data to make better decisions that sustain efficiency and risk management. The increased dependence on digital platforms, mobile banking, online payments, and fintech services has increased the pressure for sophisticated analytics in financial institutions.

Global programs such as Digital India, the Jan Dhan–Aadhaar–Mobile (JAM) trinity, the Unified Payments Interface (UPI), and expansion of digital lending programs have significantly enhanced data generation in the Indian financial ecosystem. As noted by the Reserve Bank of India (RBI, 2023), billions of digital transactions are registered in India every year, generating complex datasets that require advanced analytical tools for monitoring, compliance, and strategic planning. Although investment in analytics infrastructure has been massive, the real implementation and efficient utilization of Big Data Analytics at the employee level is not uniform across financial institutions.

According to the existing literature, success in analytics implementation does not only relate to technological availability but also to human, behavioural, and task-related factors. Usefulness, ease of use, fit between analytics systems and job tasks, and the nature of analytics technologies are all reportedly decisive factors in adoption outcomes. Thus, the adoption of Big Data Analytics should be approached as an integrated theory combining behavioural acceptance theories with task-technology alignment views.

More than efficiency in operations, Big Data Analytics has emerged as a strategic requirement for financial institutions because of growing market volatility, sophistication of customers, and regulatory complexity. The Indian financial sector is challenged by increased rates of cyber fraud, stressed assets, financial inclusion requirements, and competition from fintech companies. Big Data Analytics allows institutions to shift from a reactive to a proactive and predictive decision-making stance. As reported by the McKinsey Global Institute (2018), data-driven financial organisations have a much higher probability of acquiring and retaining customers and being more profitable compared to their less-analytical counterparts.

B. Review of Literature

Literature on the acceptance of Big Data Analytics has been documented on a broad range of academic fields, such as information systems, management science, organizational behaviour, and financial technology. The initial research aiming at technology adoption mostly concentrated on organizational readiness and infrastructure investment, but current research recognizes the significance of individual perceptions and task compatibility in explaining the failure or success of technology adoption (Venkatesh et al., 2003).

The adoption of analytics in financial institutions is influenced by regulatory forces, competition, sensitivity to risk, and workforce diversity. Chandani et al. (2015) noted that customer segmentation and operational efficiency were observed in Indian banks that embraced analytics at an early stage, but that these banks also faced resistance among workers who did not understand data-driven decision making. Similarly, Ali et al. (2020) opined that analytics adoption remains imperfect when organizations do not tackle behavioral and task-associated impediments.

Available literature shows that there is a progressive transition from a technology-based to a human-based and activity-based viewpoint of analytics adoption (Dwivedi et al., 2024). Early work focused on infrastructural readiness, data quality, and system structure, presupposing that technical capability alone would drive adoption. More recent research appreciates that technology adoption is a socio-technical process influenced by human perceptions, organizational culture, and work practices (Venkatesh et al., 2003; Dwivedi et al., 2024).

This shift is especially applicable to the financial sector since employees often base their decision-making on experience rather than algorithmic results. Daradkeh (2019) and Gangwar (2020) also highlight that analytics adoption depends on trust in data, belief in system functioning, and perceived applicability to the job. Indian studies further emphasize that resistance to analytics is not only rooted in fear of job loss or inability to use technology but also in the inability to interpret analytical outputs (NASSCOM, 2022).

C. Technology Acceptance Model (TAM)

One of the most widely used models of information system acceptance at the individual level is the Technology Acceptance Model (Davis, 1989). TAM proposes that two beliefs determine an individual's intention to use technology, namely Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) (Chatterjee & Kar, 2024). Perceived usefulness reflects users' beliefs about how a system improves job performance, whereas perceived ease of use reflects the degree to which a system is perceived as simple to use.

TAM is especially applicable in the Indian financial sector, where employees possess varying technological skills. Both public and private banks employ a mix of digitally native professionals and those familiar with legacy systems. Verma, Bhattacharyya, and Kumar (2018) found that perceived usefulness had a strong impact on analytics adoption among Indian managers, with analytics output associated with performance indicators such as reduced non-performing assets and shortened credit approval time. RBI reports similarly show that analytics-based early warning systems have enhanced asset quality management, supporting adoption decisions through perceived usefulness.

Perceived ease of use plays a complementary role. According to NASSCOM (2022), Indian banks are increasingly focusing on analytics platforms, but adoption is constrained by system complexity and insufficient analytics skills. These results suggest that enhancing usability and lowering cognitive load can raise adoption intentions.

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D. Task–Technology Fit (TTF) Model

The Task-Technology Fit model, introduced by Goodhue and Thompson (1995), highlights that individuals are more likely to use technology and achieve better results when the capabilities of the technology match the tasks that must be performed (Tarafdar et al., 2024). In contrast to TAM, which emphasizes user perceptions, TTF focuses on the functional compatibility between job requirements and system features.

Credit appraisal, fraud monitoring, compliance reporting, and portfolio analysis are activities that require timely, precise, and actionable information from financial institutions. Research by Indriasari et al. (2019) indicates that banks with task-specific analytics systems reported higher system utilization and user satisfaction. Analytics tools consistent with regulatory and operational activities, such as anti-money-laundering detection and transaction monitoring, have proven to be more readily adopted in India (RBI, 2022). These results confirm that task-technology fit is a determinant crucial to analytics adoption, especially in complex and regulated decision-making environments.

F. Integration of TAM and TTF

Combining TAM and TTF gives a more complete explanation of Big Data Analytics adoption by integrating both behavioural perceptions and task alignment. While TAM explains why users would be willing to adopt technology, TTF explains the ability of the technology to support their work effectively. Dishaw and Strong (1999) showed that adoption models combining TAM and TTF increase the level of explained variance.

Gangwar (2020) also affirmed that task-technology fit not only directly affects the intention to use analytics but also indirectly determines adoption through perceived usefulness and perceived ease of use. This combined approach is especially applicable to studying BDA adoption in financial institutions, where both user attitudes and task compatibility play a pivotal role in effective implementation.

G. Adoption of Big Data Analytics by Financial Institutions

Big Data Analytics adoption can be defined as the degree of acceptance of analytics systems, their daily usage, and incorporation into organizational decision-making. Adoption refers to both first-time implementation and long-term use, dependency on analytics results, and integration into strategic planning.

Adoption of analytics in Indian financial institutions has been growing rapidly in digital payments, credit scoring, fraud detection, and regulatory compliance, though there is significant variation across institutions and employee groups. Gangwar (2020) notes that adoption rates increase when systems are seen as useful, easy to use, and aligned with job activities.

Perceived usefulness is characterized as the degree to which a person believes that working with Big Data Analytics improves job performance (Davis, 1989). Analytics tools are viewed as helpful in Indian banking when they enhance decision speed, precision, and risk control. HDFC and ICICI banks, for example, rely on analytics-based credit scoring systems to minimize default risk and enhance loan quality, and employees exposed to these systems tend to view analytics as integral to their work. Verma et al. (2018) provide empirical evidence that perceived usefulness helps predict analytics adoption among Indian professionals.

Perceived ease of use refers to the extent to which one believes that using a system will require little effort. Analytics uptake in India is also limited by system complexity, and non-technical employees may struggle with advanced platforms. NASSCOM (2022) found that usability and training played a significant role in the range of analytics acceptance in Indian BFSI organizations, with higher adoption in banks that launched user-friendly dashboards and structured training documents.

Task-Technology Fit outlines the correspondence between technological features and job demands (Goodhue & Thompson, 1995). Analytics systems that assist specific functions such as AML monitoring, transaction analysis, and portfolio optimization are more likely to be adopted. Chandani et al. (2015) found that Indian banks using task-specific analytics applications achieved higher efficiency and user acceptance, while fintech partnerships have further improved task alignment by providing real-time analytics for online payments.

H. Relationship between Independent Variables and BDA Adoption

The integration of Big Data Analytics (BDA) in financial institutions is determined by the interaction of behavioural perceptions, task fit, and technological capability. Previous research on information systems and financial technology shows that no single determinant leads to adoption; rather, several determinants interact to shape users' desire and capability to use analytics systems. Perceived Usefulness, Perceived Ease of Use, Task-Technology Fit, and Technology Characteristics are the independent variables in this study that affect Big Data Analytics Adoption, the dependent variable.

Perceived usefulness relates to the degree to which users feel that Big Data Analytics improves workplace performance, decision accuracy, and productivity (Chatterjee & Kar, 2024). Within TAM, perceived usefulness has been established as one of the strongest predictors of technology adoption (Davis, 1989). Users respond more positively to analytics systems when they see tangible improvements in decisions, error reduction, or efficiency, particularly given the high financial risk and regulatory responsibility inherent in financial institutions. Empirical research on the banking sector indicates that employees embrace analytics tools most when they observe tangible changes in decision quality (Verma et al., 2018), and Indian evidence shows that analytics-supported early warning systems improve asset quality and employee confidence in analytics utility (RBI, 2023).

Perceived ease of use is the extent to which users believe minimal effort is required to utilize Big Data Analytics. TAM postulates that even useful systems will not be adopted if viewed as complex (Davis, 1989); ease of use lessens cognitive load, lowers resistance, and improves user confidence. Skill gaps and system complexity remain challenges to analytics adoption in the Indian financial sector, and studies show that employees are more willing to use systems with user-friendly dashboards, automatic reporting, and visual data display (Daradkeh, 2019; NASSCOM, 2022). Perceived ease of use also indirectly enhances perceived usefulness, since systems regarded as easy to use are more likely to be regarded as useful.

Task-Technology Fit (TTF) refers to the degree to which the abilities of Big Data Analytics systems match the specific tasks performed by employees. Goodhue and Thompson (1995) argue that technology will be embraced and effectively utilized when it suits users' job needs. Credit evaluation, fraud monitoring, portfolio analysis, and regulatory reporting all require timely, accurate, and relevant data support. Chandani et al. (2015) found that Indian banks with task-oriented analytics tools showed greater effectiveness and user acceptance, and Gangwar (2020) confirmed that task-technology fit is a crucial factor that also improves perceived usefulness and system relevance.

Technology characteristics are the predetermined features of Big Data Analytics systems, such as data accuracy, system reliability, scalability, integration capability, and security (RBI, 2024). These traits form the infrastructure that advances or limits adoption and are especially vital in the highly regulated finance industry, where reliability and data safety are critical. Research shows that strong technology features positively affect user trust and adoption (Yen et al., 2010; RBI, 2024), and this significance is amplified in the Indian context by RBI's data governance and cybersecurity requirements. Gangwar (2020) found that strong technology characteristics directly affect adoption while also increasing perceived usefulness and ease of use.

Collectively, the literature suggests that Big Data Analytics adoption in financial institutions results from the combined influence of perceived usefulness, perceived ease of use, task-technology fit, and technology characteristics. When analytics systems are perceived as useful, easy to use, well-aligned with job tasks, and technologically robust, adoption levels are significantly higher. This integrated perspective aligns with the combined TAM–TTF framework, offering a comprehensive explanation of analytics adoption that addresses both behavioural and functional dimensions.

I. Hypothesis Development

Based on the literature review and theoretical grounding, the following hypotheses are proposed:

H1: Perceived usefulness has a significant positive effect on Big Data Analytics adoption in financial institutions.

H2: Perceived ease of use has a significant positive effect on Big Data Analytics adoption in financial institutions.

H3: Task–Technology Fit has a significant positive effect on Big Data Analytics adoption in financial institutions.

H4: Technology characteristics have a significant positive effect on Big Data Analytics adoption in financial institutions.

J. Theoretical Framework

The theoretical framework integrates the Technology Acceptance Model (TAM) and the Task–Technology Fit (TTF) model (Chatterjee & Kar, 2024). TAM explains adoption through perceived usefulness and ease of use, while TTF emphasizes the importance of task alignment. Together, these models provide a comprehensive explanation of Big Data Analytics adoption in financial institutions, positing that Perceived Usefulness, Perceived Ease of Use, Task-Technology Fit, and Technology Characteristics each exert a direct effect on Big Data Analytics Adoption.

Perceived Usefulness (PU)	
Perceived Ease of Use (PEOU)	**Big Data Analytics Adoption in Financial Institutions**
Task–Technology Fit (TTF)	
Technology Characteristics (TNC)	

Fig. 1. Theoretical Framework (Source: Developed for research)

K. Research Gap

Even though Big Data Analytics (BDA) has drawn growing interest from academics and practitioners, a critical analysis of current literature shows several important gaps that should be filled by further study, specifically in the context of financial institutions in India.

First, a significant proportion of prior research focuses on organizational-level outcomes of Big Data Analytics implementation, including financial results, operational efficiencies, or competitive advantage. Although informative, these studies usually do not consider the individual-level adoption behaviour of the employees who directly engage with analytics systems daily. Very little effort has been invested in how employees perceive and understand analytics tools, how these perceptions affect adoption decisions, and why resistance persists despite large organisational investment.

Second, despite the common use of the Technology Acceptance Model (TAM) and Task-Technology Fit (TTF) model to study information systems adoption, the literature lacks a unified application of both models to provide a holistic explanation of Big Data Analytics adoption (Chatterjee & Kar, 2024). Studies relying solely on TAM address perceived usefulness and ease of use but do not sufficiently address whether analytics systems align with employees' job activities, while studies based solely on TTF concentrate on system-task alignment without capturing behavioural and perceptual variables. This disjointed methodology restricts the explanatory ability of prior research, especially in a complex setting such as a financial institution where both behavioural acceptance and work fit are essential.

Third, the Indian financial setting presents a variety of regulatory, operational, and technological challenges that are not sufficiently discussed in current literature (RBI, 2024). Indian financial institutions are highly regulated by the Reserve Bank of India regarding data governance, cybersecurity, and compliance reporting. Although international studies recognize the role of technology characteristics, empirical research is lacking on the effect of features such as data security, system reliability, scalability, and integration capability on analytics adoption within the Indian regulatory environment.

Fourth, previous studies have focused more on private-sector banks and fintech institutions and scarcely on government-owned banks, which lead the Indian financial system. Public sector banks have large, diversified customer bases and significant assets under management, but face constraints such as legacy systems, rigid organizational structures, and varying workforce skill levels. The limited empirical research dedicated to analytics application in public sector banks hinders the generalizability of results.

Finally, most current research uses cross-sectional designs and limited sample sizes, preventing observation of contextual and behavioural differences across institutions and employee groups. To fill these gaps, the current paper proposes a combined TAM–TTF approach to investigate individual-level adoption of Big Data Analytics with reference to technology characteristics and task alignment in the Indian financial environment.

III. Research Methodology

A. Introduction

Research methodology governs the way theoretical ideas are converted into measurable and observable entities. While the literature review provided a holistic conceptual basis for understanding Big Data Analytics (BDA) adoption in financial institutions, this section describes the manner in which this understanding is empirically investigated through a systematic, scientifically grounded research process.

Unlike traditional technology adoption, the adoption of Big Data Analytics implies complex cognitive judgment, task execution, and institutional responsibility, particularly within a highly regulated setting such as banking and financial services (Rai et al., 2023). The regulatory oversight of Indian financial institutions, enormous transaction volumes, and rising demand for analytics-driven decision making make employee-level adoption a decisive driver of organizational benefit. According to prior research, despite massive investments in analytics infrastructure, organizations often fail to realize maximum value due to low user adoption and poor integration with daily work habits (LaValle et al., 2011; Dwivedi et al., 2024).

B. Operational Definitions of Research Variables

Operational definitions are essential for converting abstract theoretical constructs into measurable variables (DeVellis, 2017). Each construct in this study is defined both conceptually and operationally as follows.

Perceived Usefulness (PU): the degree to which employees believe that use of Big Data Analytics improves job performance (Davis, 1989), operationalized through perceptions that BDA improves decision accuracy and speed, enhances effectiveness in handling complex financial data, supports risk identification, and contributes to individual and departmental performance (Verma et al., 2018; Gangwar, 2020; Chatterjee & Kar, 2024).

Perceived Ease of Use (PEOU): the extent to which employees believe that using Big Data Analytics systems involves minimal effort (Davis, 1989), operationalized through ease of learning, clarity and intuitiveness of interfaces, simplicity of interpreting outputs, and effort required for daily integration (Daradkeh, 2019; NASSCOM, 2022).

Task–Technology Fit (TTF): the degree to which the capabilities of a technology align with the tasks performed by users (Goodhue & Thompson, 1995), operationalized through the relevance of information provided, improvement in task efficiency, and support for decision-making requirements specific to financial operations (Dishaw & Strong, 1999; Indriasari et al., 2019; Gangwar, 2020).

Technology Characteristics (TC): the inherent features of Big Data Analytics systems, including data accuracy, system reliability, security, scalability, and integration capability, operationalized through employee perceptions of data accuracy and consistency, system reliability and uptime, security safeguards, and compatibility with core banking systems (Yen et al., 2010; Rai et al., 2023; RBI, 2024).

Big Data Analytics Adoption (BDAA): the degree to which employees embrace, use frequently, and depend on analytics tools in their work behaviours, operationalized through frequency of system usage, dependence on analytics outputs for decision-making, and integration of analytics into routine workflows (LaValle et al., 2011; Dwivedi et al., 2024).

C. Research Framework and Hypotheses

The research framework connects theory with empirical investigation by adopting the integrated Technology Acceptance Model (TAM) and Task-Technology Fit (TTF) model to describe Big Data Analytics adoption in financial institutions. The model assumes that Perceived Usefulness, Perceived Ease of Use, Task-Technology Fit, and Technology Characteristics each have a direct effect on Big Data Analytics adoption, acknowledging that analytics adoption is a socio-technical process shaped by personal perceptions, task needs, and system quality (Dishaw & Strong, 1999; Gangwar, 2020). Based on this framework, hypotheses H1 through H4, presented in Section II-I above, are formulated and tested empirically.

D. Sources of Research Data

The research is based mostly on primary data, as only direct responses from employees interacting with analytics systems can adequately capture adoption behaviour (Creswell & Creswell, 2018). Primary data was collected via a structured questionnaire administered to employees working in Indian financial institutions. Secondary data in the form of academic journals, books, industry reports, and regulatory publications were used to support theory development, refine measurement scales, and interpret empirical results.

E. Sampling Design

The research uses a purposive (non-probability) sampling technique, in which respondents are selected based on their knowledge, experience, and relevance to the research issue. This method was chosen because not all employees of a financial institution interact directly with analytics systems, and including uninformed respondents would dilute data quality. Respondents were selected from positions and functions where analytics use is integral to job operations, including risk

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management, credit analysis, operations, compliance, digital banking, data analytics, and managerial decision-making. Purposive sampling is well supported in information systems and technology adoption research, which emphasizes using actual or potential system users as respondents to strengthen internal validity (Venkatesh et al., 2003; Saunders et al., 2019).

Sample size was determined with reference to the methodological guideline of 10 to 20 respondents per independent variable for multiple regression analysis (Hair et al., 2019), yielding a minimum threshold of 40–80 respondents. To improve the rigor, applicability, and validity of the results, the research targeted a larger sample of approximately 200 respondents, consistent with recommendations for multivariate behavioural research (Field, 2018). This approach reduces sampling error, improves the precision of parameter estimates, and accounts for non-response and incomplete questionnaires.

Respondents comprised employees of Indian public sector banks, private sector banks, and third-party financial institutions that have implemented Big Data Analytics as an operational, risk, compliance, or strategic support service. Specifically, respondents were managers, assistant managers, analysts, officers, and senior executives across credit appraisal, risk management, operations, compliance, digital banking, data analytics, and business intelligence functions. This selection ensures alignment between the individual-level unit of analysis and the research objectives, a key requirement for methodological rigor in behavioural research (Venkatesh et al., 2003; Hair et al., 2019).

F. Research Instrument and Data Collection

A structured questionnaire served as the primary research instrument, comprising a demographic and organizational details section (Section A) and measurement items for PU, PEOU, TTF, TC, and BDA Adoption (Section B). All items were measured using a five-point Likert scale, widely accepted in behavioural and management research for its simplicity and reliability (Likert, 1932). Demographic variables were treated as nominal data, while Likert-scale items were treated as interval data for statistical analysis, consistent with established research practice (Hair et al., 2019).

The questionnaire was administered online primarily through Google Forms, supplemented by limited offline distribution. Respondents were informed of the academic purpose of the study, and confidentiality and anonymity were assured to minimize response bias. Prospective respondents were contacted through professional networks and institutional channels over a defined time frame to reduce variability caused by organizational or policy changes and to ensure comparable responses. Following collection, responses were screened for completeness, accuracy, and consistency, and incomplete or inconsistent responses were excluded prior to analysis.

G. Data Analysis

Data analysis was conducted using IBM SPSS Statistics, proceeding through univariate, bivariate, and multivariate stages. Univariate analysis employed frequency, percentage, mean, and standard deviation statistics to profile respondents and characterize research variables. Bivariate analysis used Pearson correlation coefficients to examine the strength and direction of relationships between the independent variables and Big Data Analytics adoption, and to screen for potential multicollinearity prior to regression analysis. Multivariate analysis used multiple linear regression to test the hypothesized relationships, estimate the relative contribution of each independent variable, control for the influence of other variables, and determine statistical significance, with the coefficient of determination (R^2) indicating the proportion of variance in adoption explained by the model.

Internal consistency of the measurement scales was assessed using Cronbach's alpha, with values at or above the accepted threshold of 0.70 indicating that items within each construct reliably measured the same underlying concept. Content validity was supported through the use of established measurement scales adapted from prior validated research, with minor contextual adjustments made for the financial sector (Rossner & Jack, 2001).

IV. DATA ANALYSIS AND RESULTS

This section presents the analysis and interpretation of the results obtained from 204 valid respondents. Data analysis was conducted using IBM SPSS Statistics through descriptive and inferential statistical methods. The section begins with the demographic profile of respondents, followed by descriptive statistics of the study variables, reliability analysis, correlation analysis, and multiple regression analysis used to test the proposed hypotheses.

A. Profile of the Respondents

Table I presents the gender distribution of respondents.

TABLE I GENDER OF RESPONDENTS

Gender	Frequency	Percent	Valid Percent	Cumulative Percent
Female	115	56.4	56.4	56.4
Male	85	41.7	41.7	98
Prefer not to say	4	2	2	100
Total	204	100	100	

The findings show that female respondents represented the majority of the sample (56.4%), with male respondents comprising 41.7% and a small proportion (2.0%) preferring not to disclose their gender. This distribution ensures that the study captures varied perspectives on the adoption of Big Data Analytics across genders.

TABLE II AGE GROUP OF RESPONDENTS

Age Group	Frequency	Percent	Valid Percent	Cumulative Percent
18–25 years	91	44.6	44.6	44.6
26–35 years	48	23.5	23.5	68.1
36–45 years	40	19.6	19.6	87.7
46–55 years	21	10.3	10.3	98
Above 55 years	4	2	2	100
Total	204	100	100	

Most respondents were in the early-career and mid-career age brackets, indicating that the research largely reflects the impressions of employees currently engaged in learning, adapting to, and using emerging technologies such as Big Data Analytics. The inclusion of older respondents also adds strategic and managerial perspectives on analytics adoption.

TABLE III WORK EXPERIENCE OF RESPONDENTS

Work Experience	Frequency	Percent	Valid Percent	Cumulative Percent
1–3 years	93	45.6	45.6	45.6
3–5 years	44	21.6	21.6	67.2
6–10 years	30	14.7	14.7	81.9
More than 10 years	37	18.1	18.1	100
Total	204	100	100	

A high percentage of respondents had moderate professional experience, with the remainder possessing lower experience. This implies that the sample consists of employees conversant with organisational processes and decision-making, while the presence of both less-experienced and highly-experienced respondents strengthens the credibility of the research by reflecting varying degrees of exposure to analytics systems.

TABLE IV EDUCATIONAL QUALIFICATION OF RESPONDENTS

Qualification	Frequency	Percent	Valid Percent	Cumulative Percent
Diploma	3	1.5	1.5	1.5
Bachelor's Degree	82	40.2	40.2	41.7
Master's Degree	102	50	50	91.7
Doctorate	17	8.3	8.3	100
Total	204	100	100	

Most respondents hold undergraduate or postgraduate degrees, with a smaller proportion holding doctorate qualifications. This academic profile suggests that respondents possess a strong capacity to interpret and apply sophisticated analytical tools, contributing to informed adoption decisions in financial institutions.

TABLE V JOB LEVEL OF RESPONDENTS

Job Level	Frequency	Percent	Valid Percent	Cumulative Percent
Operational / Staff Level	48	23.5	23.5	23.5
Middle Level	116	56.9	56.9	80.4
Top Level	40	19.6	19.6	100
Total	204	100	100	

Respondents span operational, middle, and top-level ranks, with the majority in the operational and middle-level category, indicating that the study largely represents the opinions of employees directly involved in using analytics systems in their daily activities. Top-level respondents further provide strategic insight into technology investment and organisational analytics decisions.

B. Descriptive Statistics of Study Variables

Table VI summarizes the descriptive statistics (N, minimum, maximum, mean, and standard deviation) for the 25 measurement items (Q7–Q31) spanning the five constructs of the study.

TABLE VI DESCRIPTIVE STATISTICS OF STUDY VARIABLES

Item	N	Min	Max	Mean	Std. Dev.
Q7	204	1	5	3.8	1.014
Q8	204	1	5	3.79	0.924
Q9	204	1	5	3.79	0.935
Q10	204	1	5	3.8	0.954
Q11	204	1	5	3.84	1.015
Q12	204	1	5	3.74	0.967
Q13	204	1	5	3.87	0.974
Q14	204	1	5	3.81	0.985
Q15	204	1	5	3.86	0.978
Q16	204	1	5	3.91	0.937
Q17	204	1	5	3.69	0.931
Q18	204	1	5	3.72	0.897
Q19	204	1	5	3.73	0.984
Q20	204	1	5	3.75	0.958
Q21	204	1	5	3.7	0.95
Q22	204	1	5	3.75	0.973
Q23	204	1	5	3.83	0.921
Q24	204	1	5	3.83	0.928
Q25	204	1	5	3.83	0.98
Q26	204	1	5	3.82	0.978
Q27	204	1	5	3.69	0.981
Q28	204	1	5	3.74	0.992
Q29	204	1	5	3.8	1.004
Q30	204	1	5	3.8	0.993
Q31	204	1	5	3.87	0.986

All mean scores exceed the midpoint of the five-point Likert scale, indicating an overall positive perception of respondents toward Big Data Analytics and its determinants. The relatively high mean value for adoption items indicates that employees in financial institutions are accepting and willing to rely on analytics systems, while the tightly clustered standard deviations suggest high consistency in perceptions with no extreme outliers.

C. Reliability Analysis

Reliability analysis was performed to evaluate the internal consistency of the measurement items for each construct, using Cronbach's alpha as the standard reliability measure for behavioural and technology adoption research. Table VII summarizes the results.

TABLE VII RELIABILITY STATISTICS

Construct	Cronbach's Alpha	N of Items
Perceived Usefulness (PU)	0.921	4
Perceived Ease of Use (PEOU)	0.891	4
Task–Technology Fit (TTF)	0.866	4
Technology Characteristics (TC)	0.895	4
Big Data Analytics Adoption (BDA)	0.913	4

All constructs recorded a Cronbach's alpha value well beyond the rigor threshold of 0.70. Perceived Usefulness and

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Big Data Analytics Adoption exceeded 0.90, indicating superior reliability, while the remaining constructs also demonstrated high internal consistency. These results confirm that the measurement items are valid and suitable for further inferential analysis.

D. Correlation Analysis

Pearson correlation analysis was conducted to test the association between the independent variables and adoption of Big Data Analytics. Table VIII presents the correlation matrix.

TABLE VIII PEARSON CORRELATION MATRIX

	PU	PEOU	TTF	TC	BDA
PU	1	.767**	.732**	.675**	.682**
PEOU	.767**	1	.836**	.745**	.756**
TTF	.732**	.836**	1	.834**	.753**
TC	.675**	.745**	.834**	1	.769**
BDA	.682**	.756**	.753**	.769**	1

** Correlation is significant at the 0.01 level (2-tailed); N = 204 for all pairs.

The results show good, positive, and statistically significant associations ($p < .01$) between all independent variables and Big Data Analytics adoption, indicating that higher levels of perceived usefulness, perceived ease of use, task-technology fit, and technology characteristics are connected with greater adoption of Big Data Analytics. These results provide preliminary support for the hypotheses and justify proceeding to regression analysis to examine the relationships in more detail.

E. Multiple Regression Analysis

Multiple regression analysis was performed to evaluate the combined and individual effects of the independent variables on Big Data Analytics adoption.

TABLE IX REGRESSION MODEL SUMMARY

Model	R	R Square	Adjusted R Square	Std. Error of Estimate
1	.822	.676	.669	.48774

Predictors: (Constant), Technology Characteristics, Perceived Usefulness, Perceived Ease of Use, Task–Technology Fit.

The model summary shows that the four independent variables jointly explain a substantial 67.6% of the variance in Big Data Analytics adoption (Adjusted $R^2 = .669$), confirming that the chosen variables form a powerful explanatory model of analytics adoption behaviour among employees in financial institutions.

TABLE X REGRESSION COEFFICIENTS

Model	B	Std. Error	Beta	t	Sig.	VIF
(Constant)	0.411	0.175	—	2.349	0.02	—
PU_MEAN	0.129	0.065	0.131	1.993	0.048	2.642
PEOU_MEAN	0.287	0.081	0.29	3.565	<.001	4.061
TTF_MEAN	0.094	0.098	0.088	0.963	0.337	5.101
TC_MEAN	0.395	0.075	0.392	5.257	<.001	3.416

Dependent Variable: Big Data Analytics Adoption (BDA_MEAN).

The regression coefficients reveal that Technology Characteristics ($\beta = .392$, $p < .001$) and Perceived Ease of Use ($\beta = .290$, $p < .001$) are the strongest significant predictors of adoption, followed by Perceived Usefulness ($\beta = .131$, $p = .048$). Task–Technology Fit did not emerge as a statistically significant unique predictor in the multivariate model ($\beta = .088$, $p = .337$), suggesting that its influence on adoption is substantially mediated by its strong correlation with Perceived Ease of Use and Technology Characteristics. Overall, the findings confirm that employees tend to adopt Big Data Analytics more readily when systems are perceived as useful, easy to use, appropriately matched to job activities, and technologically robust.

V. Discussion, Conclusion and Recommendations

A. Findings of the Study

The descriptive statistical findings revealed that respondents held predominantly positive perceptions toward the application of Big Data Analytics systems within their organisational settings, reflecting the broader transformation of the financial sector toward data-oriented operations (McKinsey & Company, 2024; RBI, 2024; Dwivedi et al., 2024). Correlation analysis indicated statistically significant positive relationships between all independent variables and adoption, providing early empirical support for the theoretical assumptions of TAM and TTF (Davis, 1989; Goodhue & Thompson, 1995; Gangwar, 2020). Multiple regression analysis, controlling for the influence of other variables, confirmed that the chosen determinants together account for a significant percentage of variance in adoption behaviour, supporting a socio-technical view of technology adoption in which successful implementation depends on simultaneous user acceptance, operational relevance, and system quality (Dishaw & Strong, 1999; Dwivedi et al., 2024).

Perceived usefulness was found to have a statistically significant positive effect on adoption, confirming that employees are more willing to use analytics systems when they perceive tangible improvements in decision accuracy, productivity, and the ability to handle complex financial data. This finding is consistent with TAM's core proposition that perceived usefulness is the strongest predictor of technology acceptance (Davis, 1989) and aligns with prior banking-sector research linking analytics adoption to measurable gains such as reduced credit approval times and improved risk prediction (Gangwar, 2020).

Perceived ease of use also showed a statistically significant positive effect, indicating that analytics systems perceived as easy to learn and operate achieve higher rates of acceptance, particularly given the varying technological competencies of financial-sector employees. This supports TAM's dual-factor structure and confirms the value of intuitive dashboards, automated reporting, and simplified interfaces in promoting adoption (Daradkeh, 2019; NASSCOM, 2022).

Task–Technology Fit demonstrated a strong positive bivariate correlation with adoption, consistent with the Task-Technology Fit theory (Goodhue & Thompson, 1995), though its unique contribution in the multivariate regression model was not statistically significant once perceived ease of use and technology characteristics were accounted for. This suggests that task alignment operates substantially through, or in tandem with, usability and technological robustness rather than as a wholly independent driver in this sample.

Technology characteristics emerged as the strongest predictor of adoption in the regression model, confirming that data accuracy, system reliability, security, and integration capability are central to building employee trust in analytics outputs. This finding reflects the heightened importance of technological soundness in a highly regulated, risk-averse financial environment (Yen et al., 2010; RBI, 2024).

B. Theoretical and Managerial Implications

Theoretically, the study reinforces the applicability of the integrated TAM–TTF framework to Big Data Analytics adoption in financial institutions, demonstrating that a more complete understanding of adoption emerges when behavioural perception and functional compatibility factors are considered concurrently rather than in isolation (Dishaw & Strong, 1999). The findings extend prior literature into the Indian financial services context, characterized by rapid digitalisation, high regulatory intensity, and large transaction volumes, thereby providing context-specific empirical evidence that complements studies conducted predominantly in developed economies (RBI, 2024; Dwivedi et al., 2024).

Managerially, the results suggest that financial institutions seeking to increase analytics adoption should treat implementation as a broad socio-technical change rather than a purely technical deployment. Organisations should clearly communicate the practical performance benefits of analytics tools to reinforce perceived usefulness, invest in user-centred system design and training to enhance perceived ease of use, configure analytics platforms to departmental functions to strengthen task-technology fit, and prioritise robust data governance, cybersecurity, and system integration to build the technological trust that underlies sustained adoption (Davis, 1989; Goodhue & Thompson, 1995; Gangwar, 2020; RBI, 2024).

C. Study Recommendations

Based on the findings, the following interventions are recommended for financial institutions seeking to enhance analytics adoption:

1) Conduct ongoing analytics education and capacity-building programs that go beyond system operation training to demonstrate practical decision-making applications such as fraud detection and credit assessment.

2) Develop role-specific dashboards and personalised analytics interfaces tailored to the operational needs of different functional departments.

3) Embed analytics use into organisational performance evaluation and decision-support processes to cultivate a data-driven management culture.

4) Invest in robust cybersecurity models and data governance systems that guarantee system reliability, data security, and regulatory compliance.

5) Ensure seamless integration of analytics platforms with core banking and enterprise information systems to minimise workflow fragmentation and inefficiency.

D. Limitations of the Study

The study relied on self-reported survey data, which may be subject to social desirability bias and common method variance (Podsakoff et al., 2003). The cross-sectional design captures perceptions at a single point in time and cannot reveal how adoption behaviour evolves as employees gain further experience with analytics systems (Dwivedi et al., 2024). The empirical scope was limited to employees of financial institutions operating within India, which may limit generalizability to other sectors or geographic contexts. Finally, the study examined a defined set of variables within the integrated TAM–TTF framework; other organisational factors such as leadership commitment, digital culture, and change management practices were not included and may further explain adoption behaviour (Gangwar, 2020).

E. Scope for Future Research

Future research could employ longitudinal designs to examine how perceptions of usefulness, ease of use, task alignment, and technological trust evolve as employees gain greater exposure to analytics systems (Dwivedi et al., 2024). Comparative studies across public sector, private sector, and fintech institutions could clarify how structural and institutional differences shape adoption patterns. Extending the conceptual model to incorporate organisational variables such as leadership support, digital culture, and analytics competency, and employing mixed-method designs that combine surveys with qualitative interviews, would further deepen understanding of Big Data Analytics adoption in complex organisational settings (Gangwar, 2020; Creswell & Creswell, 2018).

F. Conclusion

This study examined the predictors of Big Data Analytics adoption among employees of Indian financial institutions using an integrated behavioural, functional, and technological approach grounded in the Technology Acceptance Model and the Task–Technology Fit framework. The empirical results demonstrate that perceived usefulness, perceived ease of use, task-technology fit, and technology characteristics are positively associated with adoption, and that perceived usefulness, perceived ease of use, and technology characteristics remain statistically significant predictors when considered jointly, together explaining 67.6% of the variance in adoption behaviour.

The findings confirm that successful implementation of Big Data Analytics requires substantially more than the deployment of sophisticated systems; it depends on the extent to which systems are usable, operationally relevant, and technologically reliable and trusted by employees managing complex financial operations. Financial institutions seeking to derive the greatest organisational benefit from Big Data Analytics should pursue an integrated approach combining user-centric system design, continuous capability development, robust cybersecurity and data governance, and close alignment of analytics outputs with operational processes. As digital transformation and data-driven decision-making continue to expand across the financial sector, understanding and managing these adoption determinants will remain critical to long-term organisational success.

REFERENCES

[1] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," MIS Quarterly, vol. 13, no. 3, pp. 319–340, 1989.

[2] D. L. Goodhue and R. L. Thompson, "Task-technology fit and individual performance," MIS Quarterly, vol. 19, no. 2, pp. 213–236, 1995.

[3] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User acceptance of information technology: Toward a unified view," MIS Quarterly, pp. 425–478, 2003.

[4] M. T. Dishaw and D. M. Strong, "Extending the technology acceptance model with task–technology fit constructs," Information & Management, vol. 36, no. 1, pp. 9–21, 1999.

[5] S. Chatterjee and A. K. Kar, "Big data analytics adoption: A combined TAM-TTF perspective," 2024.

[6] M. Tarafdar et al., "Task-technology fit in modern information systems," 2024.

[7] Y. K. Dwivedi et al., "Socio-technical perspectives on Big Data Analytics adoption," 2024.

[8] H. Gangwar, "Using TAM/TOE model to study factors affecting cloud computing adoption in Indian SMEs," 2020.

[9] Reserve Bank of India [RBI], "Report on digital transformation and data governance in Indian financial institutions," 2024.

[10] Reserve Bank of India [RBI], "Annual report: Monitoring digital transactions and systemic risk," 2023.

[11] Reserve Bank of India [RBI], "Guidelines on anti-money laundering and transaction monitoring," 2022.

[12] NASSCOM, "Adoption of analytics in the Indian BFSI sector: Challenges and opportunities," 2022.

[13] McKinsey & Company, "The impact of Big Data Analytics on the global financial services industry," 2024.

[14] McKinsey Global Institute, "Data-driven organizations and profitability in financial services," 2018.

[15] S. Verma, S. S. Bhattacharyya, and S. Kumar, "An extension of the technology acceptance model for business analytics in Indian organizations," 2018.

[16] A. Chandani et al., "Analytics adoption in Indian banks for operational efficiency and customer segmentation," 2015.

[17] M. Daradkeh, "Determinants of user acceptance of business intelligence solution: An empirical study," 2019.

[18] Ali et al., "Behavioral and task-associated impediments in analytics adoption," 2020.

[19] J. W. Creswell and J. D. Creswell, Research Design: Qualitative, Quantitative, and Mixed Methods Approaches. Thousand Oaks, CA: Sage, 2018.

[20] J. F. Hair et al., Multivariate Data Analysis. Cengage Learning, 2019.