

## **Credit Card Analysis for Financial Insights**

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Abstract-Credit card transactions generate extensive data that can be used for valuable financial insights. This project analyzes Kaggle transaction data to improve fraud detection, customer segmentation and credit risk assessment. Data records are processed in Excel, followed by structured management in SQL, and visualized in Power BI using DAX expressions to derive meaningful knowledge. Fraud detection is improved by using extended statistical models and AI control models to identify suspicious transaction patterns. Combining fraud detection, customer behavior analysis and credit risk assessment in a single analytical framework, the project provides a data control approach to help financial institutions make appropriate found decisions. The interactive Power BI dashboard allows financial analysts to pursue trends, assess risks and effectively optimize their financial strategies. This approach addresses the limitations of traditional credit card analytics by providing a scalable, automated, adaptable financial information system tailored to the developing financial environment.

#### INTRODUCTION

I.

Credit card transactions generate extensive data that, when analyzed effectively, can provide crucial financial insights. In today's dynamic financial environment, understanding consumer spending habits, transaction trends, and credit risk is essential for banks, financial institutions, and businesses. Leveraging data-driven techniques, organizations can enhance decision-making in areas such as credit approval, fraud detection, and customer segmentation.

The core aim of credit card data analysis is to derive meaningful insights from transaction records, including expenditure trends, credit utilization, repayment behavior, and risk of default. These insights help financial institutions refine their credit policies, mitigate losses from delinquencies, and design personalized financial products tailored to consumer needs. A well-structured credit card analysis enables businesses to enhance customer engagement, identify high-risk transactions, and strengthen financial stability.

As credit card usage expands, financial institutions need advanced analytical tools to interpret spending behavior, detect fraudulent activities, and evaluate financial risks efficiently. This project employs data analytics techniques to systematically process, analyze, and extract valuable insights from transaction data. Using SQL for data management, Power BI for visualization, and machine learning models for predictive analytics, it delivers a comprehensive framework for financial intelligence. By applying this analytical approach, organizations can improve fraud detection mechanisms, categorize customers based on their spending patterns, and assess credit risk with greater accuracy. The primary objective is to provide financial institutions with a scalable, data-driven solution that enhances financial decision-making and optimizes risk management strategies.

#### LITERATURE SURVEY

Extensive studies have explored credit card transaction data, emphasizing fraud detection, customer segmentation, and credit risk evaluation. This research has been instrumental in advancing analytical models that improve financial decision- making for banks and financial institutions.

• Fraud detection: Methods like isolation forests, random forests, and unsupervised clustering have been utilized to detect fraudulent transactions in real time.

• Customer segmentation: Studies have highlighted the efficiency of clustering techniques such as k-means, hierarchical clustering, and DBSCAN in categorizing customers based on their spending patterns.

• Credit risk assessment: Research has explored predictive modeling approaches, including logistic regression, deci- sion trees, support vector machines (SVMs), and ensem- ble learning models, to assess an individual's probability of credit default.

Several studies have explored credit card analytics:

## A. The role of artificial intelligence in credit analysis (K. Nguyen and L. Tran, Feb. 2024) [1]

This paper examined the role of artificial intelligence (AI) in credit analysis, highlighting how AI-powered models improve the accuracy of credit risk predictions. The study emphasized the advantages of AI in automating credit evaluation and detecting fraudulent activities in financial transactions.

## *B.* An overview of credit risk modeling in fintech (D. Patel and E. Wang, Jan. 2024) [2]

This paper conducted a comparative analysis of traditional versus machine learning credit scoring models, demonstrating that ML models outperform conventional techniques in pre- dicting creditworthiness. The study highlighted the efficiency III.

of algorithms like decision trees and neural networks in improving credit scoring accuracy.

#### C. A comparative analysis of traditional vs machine learning credit scoring models (O. Zhang and P. Chen, Dec. 2023) [3]

This paper conducted a comparative analysis of traditional versus machine learning credit scoring models, demonstrating that ML models outperform conventional techniques in predicting creditworthiness. The study highlighted the efficiency of algorithms like decision trees and neural networks in improving credit scoring accuracy.

## D. The impact of big data on credit scoring models (C. Lee, Jun. 2023) [4]

This paper explored the impact of big data on credit scoring models, emphasizing how vast datasets from diverse sources (e.g., transactional data, social media, and behavioral analytics) can refine credit assessments. The study discussed challenges in handling large-scale data and the need for robust data processing frameworks.

# E. Evaluating credit risk with machine learning algorithms (H. Kim and I. Park, May 2023) [5]

This paper evaluated credit risk using machine learning algorithms, showcasing the effectiveness of classification techniques such as support vector machines (SVM) and ensemble models. The study demonstrated how ML-based credit scoring provides higher predictive power and reduces default risks.

## F. Antecedents of Credit Card Usage Behavior: An Indian Perspective (Lin et al., May 2023) [6]

This study explores the key determinants that drive credit card adoption and usage behavior, specifically in the Indian market. Using a survey-based methodology, the study identifies psychological, economic, and demographic factors that influence consumer decisions regarding credit card utilization. The findings highlight the significance of consumer confidence, financial literacy, and promotional incentives in shaping credit card adoption.

#### G. A Study on Consumer Spending via Credit Cards (Muru-ganandam, S. S. & R. Shakthi, Mar. 2023) [7]

This paper is an analysis of consumer expenditure trends based on credit card transactions. The study examines how individuals allocate spending across different categories, identifying common patterns in transaction behavior. By analyzing transaction data, the research provides insights into customer purchasing habits and financial management strategies.

### H. Customer Awareness of Visa and MasterCard Operations (Wicker, T. M., Jul. 2022) [10]

The research investigates consumer awareness regarding Visa and MasterCard operations, focusing on the impact of marketing and advertising strategies. The study employed a pre- and post-advertising survey approach to assess how advertising influences consumer perception and brand recognition. The findings suggest that strategic marketing campaigns significantly improve consumer engagement and awareness, leading to increased credit card adoption.

### I. Enhanced Credit Card Fraud Detection Based on Attention Mechanism (Zhang, Y. et al., Sept. 2021) [12]

This paper introduces an AI-driven fraud detection system leveraging long short-term memory (LSTM) networks and attention mechanisms. The research highlights how machine learning algorithms can enhance real-time fraud detection by identifying anomalous transaction patterns. The study empha- sizes the efficacy of deep learning approaches in minimizing financial fraud and improving security measures for financial institutions.

### J. A Review of Credit Card Literature: Perspectives from Consumers (Agarwal, S. & Zhang, J., Jan 2015) [15]

This paper conducts a comprehensive review of literature on consumer decision-making processes when choosing and using credit cards. The study synthesizes insights from multiple research papers to explore how individuals evaluate credit card options, manage credit limits, and respond to financial incentives. The review also examines the long-term impact of credit card usage on financial stability.

### LIMITATIONS OF EXISTING SYSTEMS

Current credit card data analysis systems primarily focus on specific aspects of financial analysis, such as fraud detec- tion, customer segmentation, or credit risk assessment, rather than providing a holistic view of financial operations. These models typically function in isolation, limiting their ability to provide comprehensive insights for financial institutions. For example, fraud detection algorithms primarily focus on identifying suspicious transactions but do not incorporate broader customer behavior insights that could enhance fraud prevention strategies. Similarly, customer segmentation models classify consumers based on their spending habits but do not integrate fraud risk indicators or creditworthiness assessments. Furthermore, the complexity of credit card transactions, which involve high transaction volumes, diverse customer behaviors, and evolving fraudulent tactics, presents significant challenges. Many existing analytical systems are not designed to efficiently handle large, high-dimensional datasets, making it difficult to derive real-time, actionable insights. Financial institutions require scalable, efficient, and integrated systems

to address these shortcomings effectively.

### Key Challenges in Existing Systems are:

• Lack of Integration Across Analytical Models: Traditional models are designed to address individual financial aspects such as fraud detection, customer segmentation, or credit risk assessment, without integrating all these factors into a unified analytical framework. As a re- sult, financial institutions lack a comprehensive view of customer behavior, making it difficult to make data- driven decisions that account for multiple risk factors simultaneously. - **Inefficient Handling of Large Datasets:** Financial insti- tutions generate millions of transactions daily, requiring robust data processing capabilities. However, many ex- isting data analysis systems struggle with handling high- volume, high-dimensional datasets, leading to delays in identifying trends, detecting fraud, and assessing credit risk. Without efficient data processing techniques, insti- tutions may miss critical insights that could optimize their financial strategies.

• Limited Real-Time Analytical Capabilities:Most cur- rent analytical models take hours or even days to process vast amounts of transaction data. This delay reduces their effectiveness in providing real-time insights, which are essential for fraud prevention, risk assessment, and dynamic financial decision-making. Financial institutions require faster, more responsive analytical tools to detect fraudulent activities in real time and make instantaneous credit risk evaluations.

• Scalability and Performance Limitations: Many legacy financial analysis systems are not scalable, meaning they perform well under controlled conditions but fail when exposed to larger, more complex datasets. As transaction volumes grow, these systems experience degraded performance, making them unsuitable for large-scale financial institutions that need to process high-frequency transactions efficiently.

#### IV. PROBLEM STATEMENT, SCOPE, AND OBJECTIVE

#### A. Problem Statement

The lack of a unified system that seamlessly integrates fraud detection, customer segmentation, and credit risk eval- uation poses a major challenge in current financial analysis frameworks. Many financial institutions depend on distinct, specialized models for these functions, resulting in fragmented insights and operational inefficiencies. However, without a comprehensive approach, extracting meaningful financial insights from credit card transaction data remains limited.

This project seeks to address these challenges by developing a scalable, all-in-one analytical system that utilizes credit card transaction data to generate holistic financial insights. By leveraging widely used tools such as Excel, SQL, and Power BI, the system will allow financial institutions, analysts, and businesses to conduct fraud detection, customer segmentation, and credit risk assessment within a single, integrated platform. This strategy aims to enhance data-driven decision-making, strengthen fraud prevention techniques, and provide organizations with a deeper understanding of consumer spending patterns and credit risk profiles.

#### B. Objective

The primary goal of this project is to develop a datadriven analytical system for credit card transactions that enables financial institutions to gain comprehensive insights into customer behaviors, spending patterns, and credit risk. By leveraging data analytics and visualization techniques, the system will provide valuable information that supports strategic decision-making, personalized financial services, and fraud prevention measures.

## The system aims to focus on following Key Objectives:

1) Consumer Segmentation and Behavior Analysis:

• Identify distinct consumer segments based on their credit card usage patterns, spending habits, and transaction frequencies.

• Categorize customers by their financial behaviors, risk profiles, and purchasing preferences to enable better- targeted services.

2) Spending Pattern Analysis and Trend Identification:

• Examine how consumers utilize credit cards across dif- ferent spending categories such as travel, retail, dining, utilities, and entertainment.

• Detect emerging financial trends by analyzing historical and real-time transaction data, helping financial institu- tions understand market dynamics and consumer prefer- ences.

*3) Actionable Insights for Financial Institutions:* 

• Provide financial organizations with data-driven insights that help them optimize credit policies, interest rates, and reward programs based on customer behavior.

• Develop predictive models that assess financial risks, detect potential defaulters, and identify high-value cus- tomers for exclusive banking services.

4) Optimized Marketing and Product Personalization:

• Assist financial institutions in designing personalized financial products, rewards programs, and loan offerings based on customer segmentation.

• Enhance data-driven marketing strategies by tailoring promotions, offers, and credit card benefits that resonate with different consumer groups.

#### C. Scope

This study focuses on analyzing multiple aspects of cus- tomer awareness, preferences, and decision-making regarding credit card usage across different financial institutions. By examining key factors that influence consumer behavior, the study aims to provide valuable insights that can help banks and financial service providers enhance their credit card offerings, customer satisfaction, and marketing strategies.

#### 1) Customer Awareness and Preferences:

- Evaluate the level of awareness consumers have regarding various credit card services, benefits, and reward pro- grams offered by different banks.

• Identify the preferences of customers when selecting a credit card, including factors such as interest rates, annual fees, cashback offers, rewards, and additional benefits.

• Understand how promotional campaigns, advertisements, and word-of-mouth influence a consumer's decision to apply for a credit card.



#### 2) Customer Grievances and Service Issues:

. Assess common customer complaints and grievances re- lated to credit card services, such as hidden charges, highinterest rates, poor customer support, or unauthorized transactions.

Analyze feedback from users to determine pain points in credit card services and suggest improvements for better customer satisfaction and retention.

Factors Influencing Credit Card Adoption and 3) Usage:

Investigate the key factors that influence a consumer's decision to opt for a particular credit card, such as income levels, spending habits, lifestyle preferences, and financial stability.

Explore how security concerns, fraud risks, digital pay- ment trends, and banking policies affect the adoption of credit cards.

4) Comparative Analysis of Credit Card Services:

Compare the features, benefits, and terms of credit card offerings across various banks to identify the most attractive and customer-friendly options.

Provide insights into why consumers prefer certain banks over others when selecting a credit card.

#### V. PROPOSED SYSTEM

#### Α. Framework

A structured data pipeline using Power BI for visualization, SQL for data processing, and machine learning for analysis. The proposed system integrates various stages of credit card transaction analysis, including data preprocessing, real-time fraud detection, and trend analysis for financial insights.



### Fig. 1. Credit Card Analysis Framework

#### В. Methodology

Data Source: The pipeline appears to start with a 1) Credit Card Dataset. This could be a CSV, Excel, or other structured data format.

2) Data Loading: The dataset is loaded into Power BI. This suggests that Power BI will serve as the primary tool for data analysis and visualization.

Data Cleaning: The data undergoes cleaning to 3) remove errors and inconsistencies. This might involve tasks like

Handling missing values, Correcting inconsistencies, Filtering

Data Processing: Calculations and analysis are per- formed 4) on the cleaned data. This could include Aggre- gations, Transformations, Feature engineering

Visualization: Power BI is used to create various visu-5) alizations, such as: 1]

Charts: Bar charts, line charts, pie charts, etc.

2] Dashboards: Interactive dashboards to present multi- ple visualizations in a unified view.

Insights and Reports: The visualizations are used to 6) generate insights and create reports for decision-making. These insights could be related to:

Customer behavior: Understanding customer spend- ing 1] patterns, preferences, and churn rates.

Fraud detection: Identifying fraudulent transactions. 3] 21 Risk assessment: Evaluating credit risk. Marketing effectiveness: Measuring the impact of marketing cam- paigns.

VI. EXPERIMENTAL SETUP

Α. Database Details

Type: MySOL

Purpose: To store and manage credit card transactions data and customer details.

Structure: Tables will be created for:

Credit Card Data: Contains details about each credit card • (client num, card category, annual fees, credit limit, etc.).

Customer Data: Contains details about each customer and credit card transaction (client num, customer age, education level, contact, etc.).

### Dataset: Source - Kaggle

Description: The dataset consists of credit card transactions, including both fraudulent and legitimate transactions. It is structured to enable comprehensive analysis of spending behavior and transaction patterns. Format: CSV Files

#### В. Software and Hardware Setup

Software: Data Management and Analysis Tools

Power BI: For data visualization and dashboard creation. MySQL: For database management to store and query credit card transaction data.

Data Sources: Access to Kaggle datasets for Credit Card Transaction. Operating Systems: Windows 10 or later/ macOS/ Linux (depending on the software Compatibility.

### Hardware:

Computer Specifications: Processor: Minimum Intel i5 or equivalent (preferably i7 for better performance).

RAM: At least 8 GB (16 GB recommended for handling larger datasets).

Storage: SSD with a minimum of 256 GB (more is preferable for data storage).



Graphics Card: Dedicated GPU (optional, but beneficial for machine learning tasks).

#### - Network:

Network Requirements: Stable internet connection for data retrieval from Kaggle and cloud services.

Backup Solutions: External hard drive or cloud storage for data backup and recovery.

VII. IMPLEMENTATION PLAN

A phased implementation strategy involving:

1) Data Acquisition: Obtain the credit card dataset from Kaggle or another source.

2) Data Exploration: Conduct an initial exploration of the data to understand its structure, characteristics, and potential issues.

3) Data Cleaning: Apply appropriate techniques to address missing values, inconsistencies, and outliers.

4) Data Processing: Perform necessary calculations, trans- formations, and feature engineering.

5) Data Visualization: Create visualizations in Power BI to explore and communicate the data findings.

6) Insight Generation: Analyze the visualizations to iden- tify patterns, trends, and meaningful insights.

7) Report Creation: Develop reports that summarize the key findings and recommendations.

#### VIII. RESULTS AND DISCUSSION

The analysis of credit card transaction data has provided valuable insights into spending patterns, fraud detection, customer segmentation, and credit risk assessment. By leveraging data processing techniques in SQL, visualization tools in Power BI, and machine learning algorithms for predictive analytics, the project has successfully extracted meaningful financial insights.

#### A. Spending Behavior Analysis

• The insights suggest that financial institutions can tailor their reward programs to cater to specific age groups.

• Banks can optimize their marketing strategies by targeting customers with personalized offers and discounts during peak spending periods.

B. Customer Segmentation and Credit Utilization Patterns

• Clustering algorithms grouped customers into three pri- mary segments: High Spenders, Moderate Spenders, and Low Spenders.

• Banks can use segmentation insights to customize interest rates, credit limits, and reward structures for different customer groups.

#### C. Power BI Dashboard and Visualizations

• The interactive Power BI dashboard provided realtime insights.

• The dashboard allowed for dynamic filtering and drill- down analysis, making it easier to track trends and anomalies.



Fig. 2. Credit Card Customer Report - Revenue vs Gender







Fig. 4. Age Group and Revenue Analysis



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Cred	it Card T	ransaction	Report	Q4	Q3		Q2		21
Total Reven		Amount	Transaction Count 657K	Revenue			ransactio	on Count	
ard_Category	•		Sum of Annual_Fees	15M	14.0M	13.8M	14.2M	13.4M	· 166K · 164K
Blue	4,62,34,849.0	65,08,880.0	26,89,925	enu		164.2K			
Silver	55,86,343.0	8,12,092.0	1,87,505	10M		104 ZK			· 164K
Gold	24,54,073.0	3,73,785.0	56,210	5M	163.3K				
Platinum	11,35,608.0	1,61,629.0	20,665	OM	163.5K			162.8K	
Total	5.54.10.873.0	78,56,386.0	29,54,305	OM	Q1	Q2	Q3	Q4	162K

#### Fig. 5. Credit Card Transaction Report



#### Fig. 6. Revenue Breakdown by Category



#### IX. CONCLUSION AND FUTURE WORK

The project successfully demonstrated how data-driven in- sights can enhance financial decision-making for banks and credit card providers. By combining transaction analysis, ma- chine learning, and data visualization, the system provides a scalable and adaptable solution for fraud detection, customer segmentation, and risk assessment.

Future enhancements include:

Real-time tracking of spending and account activity will help organisation manage their finances more effectively.

With growing cybersecurity threats, credit card compa- nies will continue to improve fraud detection systems using AI, biometric verification, and advanced encryption techniques.

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Fig. 7. Revenue by Transaction Type and Customer Acquisition Cost

From these visualizations, key observations can be made regarding customer spending behavior, transaction trends, and revenue distribution across different categories. These insights help in assessing financial strategies and customer segmentation for improved decision-making.