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Intelligent Banking: Trend Analysis & AI-Driven Data Access

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Abstract

The paper proposes an AI-driven financial data retrieval chatbot and trend analysis dashboard to allow users to gain access to financial intelligence based on natural language questions. The dashboard monitors financial performance metrics, delivering visual analytics and predictive modelling for financial risk forecasting. The chatbot further enhances client engagement with information visualization tools and also provides personalized assistance. This solution especially helps banks to automate data gathering and trend analysis, leading to better strategic decision-making and customer interaction. Customer care is also enhanced through the chatbot.

Keywords: Intelligent Banking, Trend Analysis, and AI-Driven Data Access.

1. Introduction

The AI chatbot acts as analytics feature that collects, processes, and presents the financial information in a straightforward way. Customers can place conversational commands to get real-time and historical financial points through synthetic acuity, speech understanding. The bot interacts with clients through natural language pulling numerical information from multifarious data sources, and provides an integrated online visual dashboard that assists the employees in comprehending the inter-relationship between the financial facts and the opportunities for the employees. Designed in Carafe for backend management with Python, JavaScript powered the front-end. The AI platform offers integration for employee-focused predictive analysis of key financial metrics. The framework assigns monotonous work to machines that improves decision-making because the financial information can be processed and analyzed correctly. This is achieved by the framework, which often retrieves information that needs to be analyzed and maximizes customer engagement by giving critical financial information with lesser effort.

2. Literature Review

Christ *et al.*, (2025) [1] discusses applying knowledge graphs to generate SQL query components automatically to increase the efficiency and precision of database querying activities.

Aerts *et al.*, (2024) [7] examines the application of ChatGPT-3.5 for generating SQL exercises automatically and measures the viability of using sophisticated language models in instructional material generation.

Manikani *et al.*, (2025) [11] created a web-based auto grader based on large language models (LLMs) to evaluate SQL queries to enable automated and effective evaluation in academic environments.

Li *et al.*, (2024) [8] presents a review of natural language interfaces to databases, outlining methods through which users can query databases with the use of normal language, hence making data access more user-friendly.

Reshma, E & Remya (2017) examines various methods of developing typical dialect interfacing to databases, emphasizing the developments and challenges in enabling clients to connect with databases using regular dialect.

Xu *et al.*, (2017) presents SQLNet, a model that translates natural language input into structured SQL queries without using reinforcement learning, making training easier and more efficient.

Pal *et al.*, (2021) investigates a data-agnostic method utilizing the RoBERTa model to translate natural language to SQL queries, highlighting the flexibility of transformer-based models in comprehending various data situations.

Khadija *et al.*, (2024) introduces CHAT-SQL, a framework that applies deep learning methods in mapping natural language text to SQL queries, making database querying more accessible to non-proficient users.

Sonnadara *et al.*, (2024) [9] proposes a sequential model that understands natural language inputs to produce sophisticated SQL queries that entail multiple commands, in an attempt to fill the gap between database querying and user intent.

Feine *et al.*, (2020) [2] offers a system that is meant to engage domain experts in the development of high-quality natural language responses for chatbots. Through integration with

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existing chatbots using an API, the system enables experts to enhance responses in real-time during interactions and offers developers a sentiment-backed review dashboard to evaluate these improvements.

i). **Research into the Problem:** The financial segment calls for quick, precise, and timely access to financial data for informed decision-making. Traditional methods demand specific data and are challenging and cumbersome. In working with enormo, it may be hard to discern patterns and establish successful approaches. It is tricky to identify trends and formulate winning strategies while navigating massive amounts of customer relationships and information flow.us levels of client contacts and exchange data. To break through these challenges, a slant analysis dashboard and. In order to overcome these hurdles, a slant examination dashboard and an AI-powered chatbot are needed for budgetary information recovery. This setup will advance strides decision-making, optimize processes, separate fake exercises, and enhance client involvement, facilitating financial operations and rendering information more accessible and impactful.

   The banking sector requires rapid, precise, and real-time access to financial information in order to make sound decisions. Traditional methods are time-consuming, complex, and require specialized knowledge. It is difficult to identify trends and enhance strategies when working with huge amounts of transactional data and customer contacts. An AI-driven financial data retrieval chatbot and trend analysis dashboard are required to overcome these challenges. This solution will enhance decision-making, maximize strategies, identify suspicious activity, and boost customer interaction, simplifying financial processes and making information more accessible and actionable.

ii). **Research into Possible Solutions:** One of the solutions to the problems in the financial industry is creating a system that combines financial data retrieval, trend analysis, and strategy optimization. The system may incorporate a chatbot that allows users to obtain real-time financial information with ease through Natural Language Processing (NLP). In addition, the implementation of a trend analysis dashboard can be used to work with massive amounts of financial data to uncover trends, forecast market trends, and display insights on interactive dashboards Moreover, by analyzing past data and market conditions, AI-based financial forecasting and decision-making systems can assist companies in maximizing their financial plans. By combining these technologies, financial data can be made more actionable and accessible by enhancing decision-making, automating financial processes, and maximizing customer interaction.

iii). **Research into Existing System:** Today's financial data gathering and trend monitoring techniques are based on conventional techniques that are time-consuming, cumbersome, and involve specialized financial expertise. Most businesses and financial institutions employ manual gathering of data from various sources like stock market sites, financial reports, and trading sites, thus hindering instantaneous decision-making. Current systems largely employ standalone financial software or web sites that have users go through complicated interfaces and interpret raw data on their own.

Besides, the analysis of financial trends tends to be executed using statistical models and Excel applications, which don't allow detection of actual patterns and making informed decisions in real-time. The rule-based system fails to pick up sophisticated anomalies and necessitates continuous manual upgrades in order to remain valid.

In addition, customer interaction and service in financial services are based on conventional customer service media, e.g., phone, emails, or web-based ticketing systems, which may be time-consuming and cumbersome. Few financial institutions have AI-based chatbots or automated assistants to offer instant answers and customized financial information.

In general, the current system grapples with real-time retrieval of information, does not offer AI-backed analysis, and contains minimal fraud and customer treatment automation, all making financial decision-making less streamlined and data-dependent

3. Data Modelling

3.1. Data Gathering

The initial step is data collection. This is a critical step since the quality and amount of data collected will have a direct impact on the trend analysis level and chatbot model. Data was obtained for this project from data.gov, which offers open financial data sets from government agencies, facilitating research, analysis, and application development.

3.2. Dataset Description

Customer Dataset

Table 1: Description of Customer Dataset

Attributes	Description	Sample Data
Customer ID	Unique identifier for each customer.	1901 1902 1903
First Name	Customer's first name.	Ravi Mohan Arjun Lakshmi
Last Name	Customer's Last name.	Nair Reddy Verma
Phone	Customer's contact number (mobile).	9124977909 9578688384 8505222880
Account ID	Unique account number associated with each customer	9414120000000000 1113860000000000
IFSC Code	The bank's IFSC-Indian Financial System Code used to identify branches	PNB0005332 PNB0006715 UTI0007546
Date of Birth	Customer's date of birth in DD-MM-YYYY format	26-05-1980 18-04-1995 31-05-1972
Address	Residential address of the customer.	18, Park Street, Mumbai 98, Gandhi Nagar, Chennai
Balance	Current balance in the customer's account.	85880.83 45304.2 26468.64

Interaction Dataset

Table 2: Description of interaction dataset.

Attributes	Description	Sample Data
Interaction ID	Unique identifier for each interaction.	1 2 3
Customer ID	Refers to the unique customer identifier	1943 2499 2044
Interaction Date	Date and time of the interaction in DD-MM-YYYY HH:MM format.	04-01-2018 00:00 06-01-2018 00:00 08-01-2018 00:00
Interaction	The type of interaction channel used.	In-Person Video Call Email
Interaction Details	Describe the reason for the interaction or inquiry type	Inquired about account balance Inquired about the loan process Inquired about KYC update

Transaction Dataset

Table 3: Description of the Transaction Dataset

Attributes	Description	Sample data
Transaction ID	Unique identifier for each transaction.	1 2 3
Customer ID	Refers to the unique customer identifier	1954 2213 2303
Transaction Date	Date and time of the transaction in DD-MM-YYYY HH:MM format.	2018-01-01 00:00:00 2018-01-02 00:00:00 2018-01-14 00:00:00
Transaction Type	Type of transaction, which can be one of the following: Payment, Withdrawal, Transfer, Deposit	Payment Withdrawal Transfer
Amount	The monetary amount involved in the transaction.	11474.13 30649.74 36550.65
Merchant:	The merchant or organization involved in the transaction	Big Bazaar Saravana Stores
Channel	The mode through which the transaction was carried out, such as: Net Banking, Branch, ATM, Card, UPI, Mobile	Net Banking Branch

4. Process Flow

4.1. Process Flow Diagram

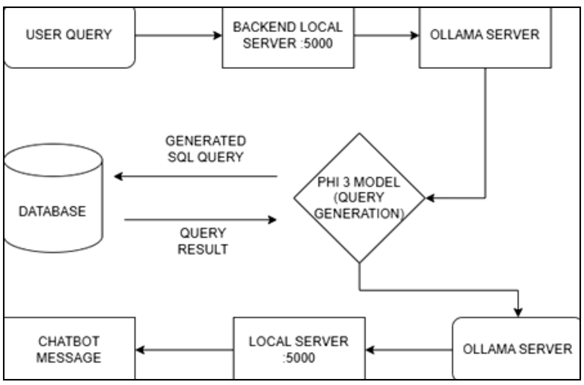

Fig 1: This figure displays the process flow of the data retrieval chatbot

Figure 6 shows the process flow of how user queries are processed, translated into SQL queries, run in the database, and returned as chatbot responses using the PHI-3 model and Ollama server. And denotes the end-to-end process flow of the Intelligent Banking Insights: Trend Analysis & AI-Driven Data Access system, with emphasis on chatbot-based financial data retrieval and dashboard-based trend analysis.

User Query Input (Chatbot Interface)
The user engages with the chatbot interface, typing a finance-related question in natural language (e.g., "What are my last 5 transactions?").

Backend Processing (Local Server – Port 5000)
The backend server (on port 5000) takes the user query and passes it to the Ollama server for processing.

Ollama Server & PHI-3 Model for SQL Query Generation
The Ollama server sends the request to the PHI-3 model, which converts the natural language request to an SQL query.
Example SQL Query Generated:
SQL: SELECT * FROM transactions WHERE user_id = ? ORDER BY date DESC LIMIT 5;

Database Query Execution
The SQL query is executed against the database, pulling the necessary financial information.

Query Result Processing
The query response (e.g., transaction information, balance, or trend analysis information) is sent back to the backend server.

Response Processing & Chatbot Message Generation
The backend processes the response in natural language and sends it back to the chatbot interface for rendering.
Dashboard Interface Integration
The data fetched is also passed on to the dashboard interface, where it is rendered for trend analysis, fraud detection, or financial insights.

5. Implementation

5.1. Phase – I

User Interface

The construction of the dashboard interface through HTML, CSS, and JavaScript is the initial step of the Intelligent Banking Insights project. This is a precursor to developing an interactive, friendly interface that users can use in order to see and analyze money data effectively.
The dashboard is the front-end interface and displays current information on financial analysis, spending trends, account balances, and client activity. It provides a smooth user experience and is responsive, visually stunning, and easy to use.

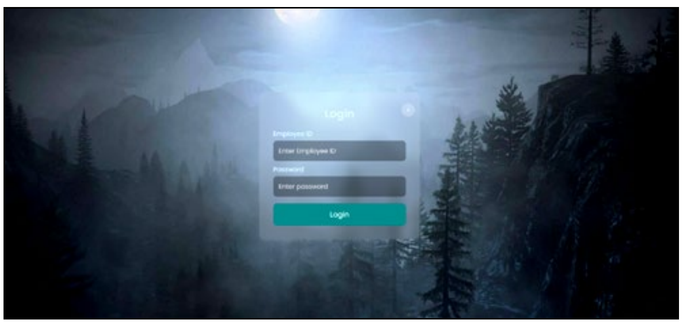

Fig 2: This Figure shows the login page of the web application

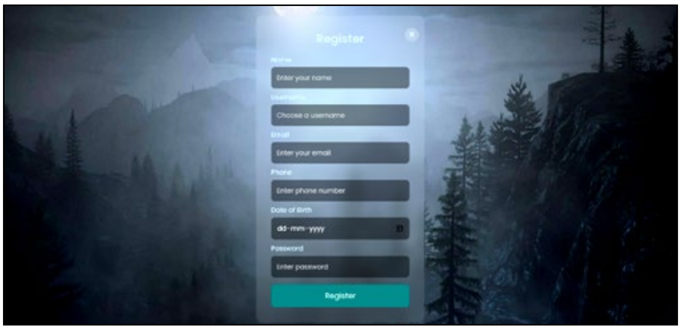

Fig 3: This Figure shows the registration page of the web application

Dashboard

Fig 4: This figure shows the trend analysis dashboard page of the web application

Fig 5: This figure shows the line graph that displays monthly customer interactions for the year 2022

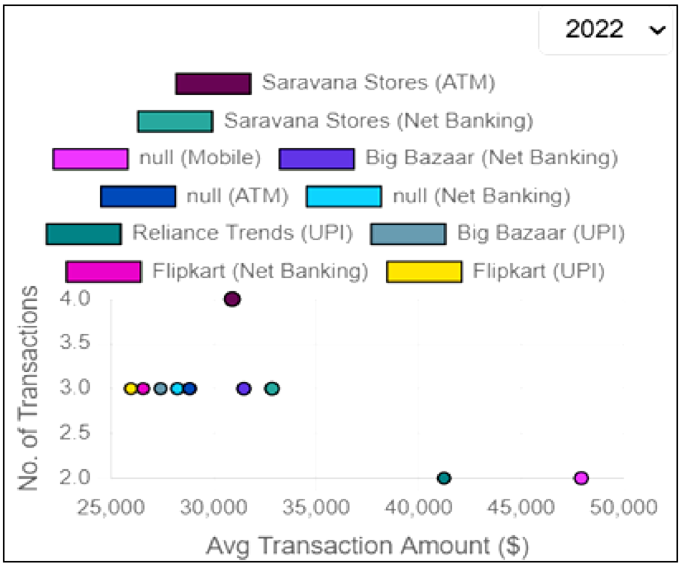

Fig 6: This figure is a scatter plot that displays transaction data for 2022. It compares average transaction amounts and the number of transactions across different vendors.

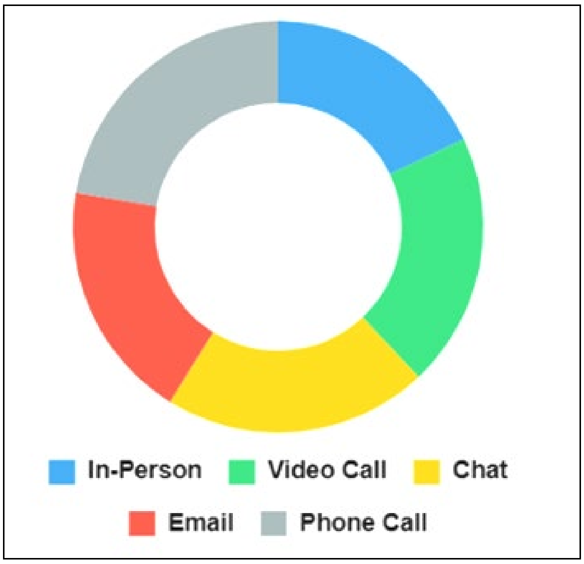

Fig 7: This figure is a donut chart that represents the distribution of customer interaction methods.

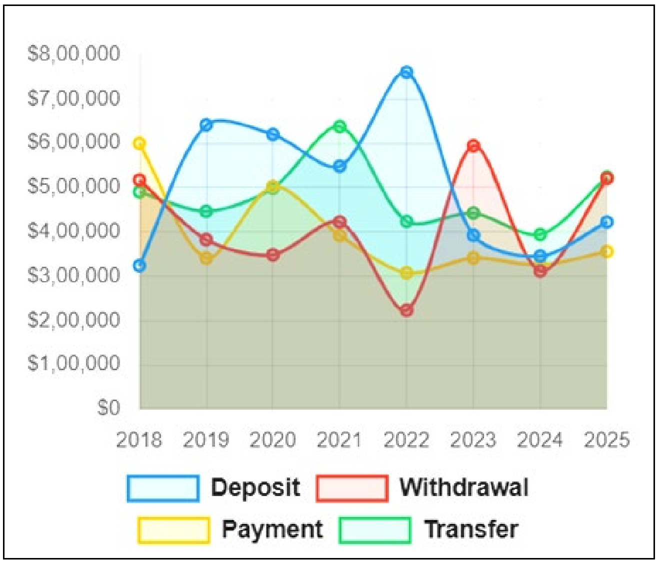

Fig 8: This figure is a financial trend chart displaying four different transaction types over the years 2018 to 2025

5.2. Phase II
Chatbot

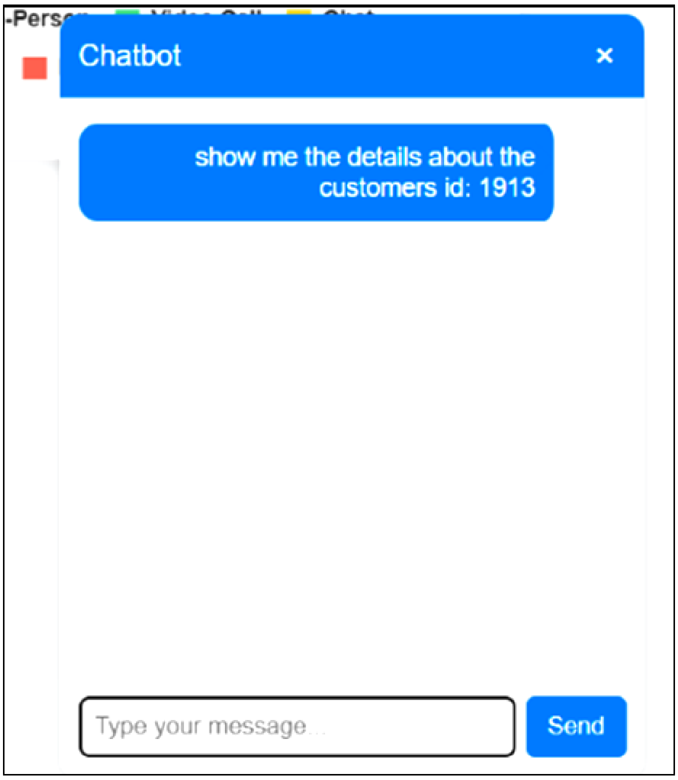

Fig 9: This figure shows a chatbot interface where a user has entered a query requesting customer details

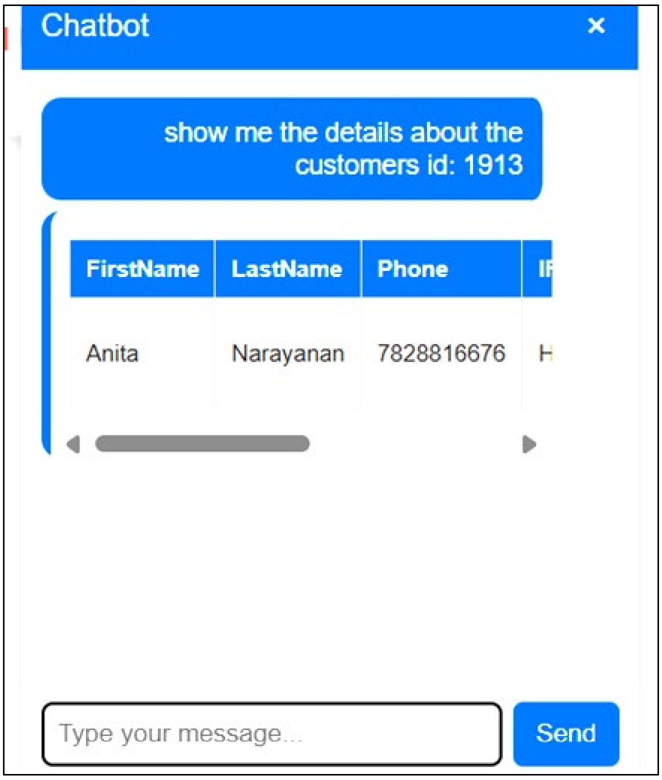

Fig 10: This figure shows an updated chatbot interface, where the chatbot has successfully retrieved and displayed customer details in response to the user's query

6. Model Evaluation

Assessment of the AI financial data retrieval chatbot and trend analysis dashboard performance is critical to guarantee accuracy, efficiency, and user satisfaction. The following were considered during model evaluation:

Accuracy of Data Retrieval: The system Retrieved Accurate financial information from the database successfully, with accuracy in response. The accuracy was maintained by matching AI responses with real SQL queries, with a high rate of correctness.

Evaluation Metric Used

SQL Query Validation-SQL query validation guarantees that a SELECT statement employed for data retrieval in MySQL is accurate, secure, and optimized. NLP-based chatbot that translates natural language into SQL queries for data retrieval from MySQL, query validation is important to guarantee accuracy, security, and efficiency

- **Data Fetching Time:** The mean time to retrieve data was 8 seconds, providing relatively swift access to financial information. Latency can be minimized further by using

optimization methods like indexing, query optimization, and caching.
Evaluation Metric Used: Response Time (measured in seconds).

- **Trend Analysis Effectiveness:** The system accurately detected important financial trends, outliers, and customer interaction trends. The dashboard offered easily interpretable visual analytics (graphs, charts) for rapid results interpretation.

Evaluation Metric Used
Visualization Accuracy and Validation
Data Accuracy
Definition: Ensures that the visualized data correctly represents the actual dataset from the database (MySQL).
Validation Approach: Cross-check raw data vs. displayed data using console logs and database queries.

Consistency and Integrity
Definition: Ensures that data remains accurate across different filters, time ranges, or user interactions.
Validation Approach: Check whether filters and search queries correctly update the visualizations. Verify real-time updates by comparing new database entries with dashboard updates.

Visualization Accuracy
Definition: Ensures that charts, graphs, and tables are correctly rendering the data.
Validation Approach: Compare visual outputs with manually calculated data.

User Interaction & UX Testing
Definition: Ensures that dashboard elements like filters, tooltips, and hover effects work smoothly.
Validation Approach: Use A/B testing to see which layouts improve usability.

Conclusion

The artificial intelligence (AI)-powered natural language processing (NLP) chatbot and trend analysis dashboard revolutionize financial data management with instant access and real-time data. The NLP chatbot allows users to fetch customer data, transactional history, and financial data easily without direct database access. It accomplishes this by converting human requests into correct SQL statements, thus eliminating the necessity of direct database interactions and providing easy-to-use financial data retrieval. To enable customers to visualize trends, anomalies, and patterns through time, the interactive trend analysis dashboard also provides key financial information, such as deposits, withdrawals, payments, and transfers, in dynamic visualizations.

With the capability to monitor cash flow, enhance financial health, and detect abnormalities in real-time, this platform enhances decision-making through structured response and graphical analytics. The ability of the chatbot to render data into organized tables also folds into a seamless user experience for financial experts as well as technical novices. Furthermore, employing automation and AI-driven analytics simplifies the process of financial monitoring, hence effort minimization and optimization of efficiency.

To take the system forward, technologies like predictive analytics with AI, enhanced search and filtering, and real-time synching with third-party sources of financial information would take the capability level of this system forward. Utilizing AI, NLP, and visualizations, these chatbot and dashboard functions represent a highly powerful, easy-to-use, and smart instrument of financial management allowing users to make informed choices in a timely and accurate manner.

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