

SmartCost: Customer Behavior Analysis & Sales Insights System for Micro-SMEs

K.A.C.H Kodithuwakku

Faculty of Computing

*Sri Lanka Institute of Information
Technology*

Malabe, Sri Lanka

IT22544872@my.sliit.lk

D.D.M Jayasingha

Faculty of Computing

*Sri Lanka Institute of Information
Technology*

Malabe, Sri Lanka

IT22162250@my.sliit.lk

N.K.M.Perera

Faculty of Computing

*Sri Lanka Institute of Information
Technology*

Malabe, Sri Lanka

IT22151810@my.sliit.lk

M.P.J.R.Dasanayake

Faculty of Computing

*Sri Lanka Institute of Information
Technology*

Malabe, Sri Lanka

IT22152664@my.sliit.lk

Deemantha Siriwardana

Faculty of Computing

*Sri Lanka Institute of Information
Technology*

Malabe, Sri Lanka

deemantha.s@sliit.lk

Ayesha Wijesooriya

Faculty of Computing

*Sri Lanka Institute of Information
Technology*

Malabe, Sri Lanka

ayesha.w@sliit.lk

Abstract—Small and medium-sized enterprises (SMEs) increasingly depend on Point of Sale (POS) systems to manage daily sales operations. However, many existing POS solutions focus primarily on transaction processing and lack intelligent analytical capabilities for evaluating customer behavior and generating actionable sales insights. This research proposes a Customer Behavior Analysis and Sales Insights system that applies transactional data mining and business analytics techniques to extract meaningful patterns from historical sales data. The proposed system identifies customer purchasing behavior, top-performing and slow-moving products, peak sales periods, and product association patterns to support data-driven decision-making. The system was evaluated using a simulated bakery and café dataset containing 15,420 transactions, 128 products, and 12 months of sales records. Experimental results achieved 91% accuracy in identifying customer and sales trends, with association rule confidence averaging 82%. The generated insights improved inventory optimization by 18% and sales performance by 11%, demonstrating the effectiveness of intelligent analytics for enhancing SME operational efficiency and strategic business planning.

Keywords—Customer Behavior Analysis, Sales Insights, Data Mining, Business Analytics, Point of Sale Systems, SME Analytics, Decision Support Systems.

I.INTRODUCTION

Small and medium sized enterprises (SMEs) play a significant role in economic development by contributing to employment generation, local business growth, and market diversification. In sectors such as retail, bakeries, and cafés, SMEs rely heavily on daily customer transactions to sustain operations and generate revenue. Despite their importance, many SMEs continue to operate with limited access to intelligent analytical systems capable of supporting strategic and operational decision making. Traditional point of sale (POS) systems are primarily designed for transaction processing and billing operations, providing only basic reporting functionalities with limited analytical capabilities. As a result, valuable transactional data generated through daily business operations often remains underutilized.

One of the major challenges faced by SMEs is the inability to transform raw transactional data into meaningful business insights. Although POS systems continuously capture information such as product identifiers, quantities sold, timestamps, and transaction values, this data is commonly used only for revenue summaries and billing records. Business owners frequently rely on manual decision making and intuition when identifying customer purchasing trends, sales performance patterns, and operational inefficiencies. This limitation reduces the ability of SMEs to optimize inventory management, improve customer engagement, and develop effective marketing strategies.

Another important challenge is the lack of integrated analytical solutions specifically designed for SME environments. Existing business intelligence platforms such as Tableau and Power BI provide advanced analytical capabilities; however, these systems are often expensive, technically complex, and difficult to deploy within resource constrained business environments. Many SMEs lack the technical expertise necessary to configure and maintain enterprise level analytics platforms. Furthermore, fragmented operational systems, inconsistent data formats, and limited computational resources create additional barriers to adopting intelligent analytics solutions.

The rapid growth of big data technologies and analytical frameworks has emphasized the importance of collecting, processing, and analyzing large volumes of operational data to gain competitive advantages [4], [5]. In this context, data mining and machine learning techniques have become increasingly important for extracting hidden patterns and trends from transactional datasets [1]–[3]. These analytical approaches enable organizations to move beyond descriptive reporting and adopt insight driven decision making strategies.

Customer behavior analysis has emerged as a critical component of intelligent retail analytics systems. Data mining techniques such as association rule mining,

clustering, and statistical aggregation are widely utilized to analyze purchasing behavior and identify hidden customer trends [1], [2], [12]. Association rule mining techniques can identify products frequently purchased together, supporting cross selling and promotional strategies [7]. Similarly, clustering and trend analysis methods enable businesses to identify customer segments, seasonal demand fluctuations, and peak sales periods that support operational optimization and marketing decision making.

Temporal analysis also plays an important role in understanding customer behavior patterns. Customer purchasing activities frequently vary based on time related factors such as hours of the day, weekdays, weekends, and seasonal events. By analyzing these temporal patterns, businesses can optimize staffing schedules, production planning, and inventory allocation. Understanding these trends enables businesses to improve operational efficiency and customer satisfaction.

Despite the availability of advanced analytical techniques, many existing POS systems continue to focus primarily on transaction processing rather than intelligent analytics. Most SME focused POS platforms provide only basic reporting capabilities without supporting integrated customer behavior analysis, sales trend analysis, dashboard analytics, and decision support functionalities. Existing business intelligence systems are often designed for enterprise scale organizations and require significant financial investment and technical expertise [9]. Consequently, there remains a significant gap in lightweight and scalable analytical systems specifically tailored for micro SME environments.

Modern technologies such as MongoDB, FastAPI, Node.js, and React Native provide practical solutions for developing scalable and integrated analytical platforms [17]–[20]. MongoDB supports flexible schema management for transactional datasets, while FastAPI and Node.js enable efficient API based communication between operational and analytical services. React Native further supports the development of lightweight and cross platform mobile applications suitable for SME environments.

A. Research Objectives

The primary objective of this research is to develop an integrated Customer Behavior Analysis and Sales Insights system capable of transforming transactional data into actionable business intelligence for SMEs. Specifically, the research aims to develop a lightweight analytics framework for customer behavior analysis, perform sales trend analysis using historical transactional datasets, generate actionable business insights through analytical and statistical techniques, develop dashboard-based visualization components for presenting analytical information, and support operational and strategic decision-making through integrated analytical functionalities.

B. Main Contributions

The major contributions of this research include the development of a lightweight SME-focused analytics framework capable of transforming transactional data into meaningful business insights, an integrated POS intelligence architecture that combines customer behavior analysis with sales insight generation, and a scalable dashboard-based analytical system designed for low-resource retail environments. Furthermore, this research provides a low-cost and practical analytics solution tailored for small and medium-sized enterprises with limited technical expertise and computational resources, enabling data-driven decision-making and improved operational efficiency.

In conclusion, the increasing importance of data driven decision making highlights the need for intelligent systems capable of transforming raw transactional data into meaningful operational insights. The proposed system demonstrates how data mining and analytical techniques can be effectively integrated into POS environments to provide scalable and accessible business intelligence solutions for resource constrained SME operations.

II. LITERATURE REVIEW

The evolution of point of sale (POS) systems reflects the broader transformation of business technologies from simple transaction recording tools into integrated digital business platforms. Early POS systems were primarily developed to automate billing operations and maintain sales records with limited capabilities for analytical processing. Although modern POS platforms provide improved reporting and inventory functionalities, many SME focused systems remain operational tools rather than intelligent analytical platforms. Most existing systems prioritize transaction speed and operational efficiency while providing minimal support for customer behavior analysis, sales trend identification, and business intelligence generation.

The increasing growth of transactional data and advancements in big data technologies have created significant opportunities for organizations to improve decision making through analytical intelligence. Big data frameworks and analytical systems enable businesses to process large volumes of operational data to gain competitive advantages and improve strategic planning [4], [5]. Data mining and machine learning techniques have become essential components of modern analytical systems, enabling organizations to discover hidden relationships, customer purchasing patterns, and operational trends from large datasets [1]–[3].

Customer behavior analysis has become an important research area within retail and business analytics environments. Data mining techniques such as clustering, classification, and association rule mining are widely utilized to analyze customer purchasing activities and identify hidden transactional relationships [1], [2], [12]. Association rule mining, introduced by Agrawal and Srikant [7], enables the identification of products frequently purchased together,

supporting cross selling and promotional strategies. Similarly, clustering techniques enable businesses to identify customer segments and purchasing groups that can support personalized marketing and operational planning.

Temporal analysis is another important component of customer behavior analytics. Sales patterns frequently vary according to time related factors such as hours of the day, weekdays, weekends, and seasonal periods. Temporal aggregation and trend analysis techniques enable organizations to identify peak sales periods, demand fluctuations, and product performance variations over time. Such insights support inventory optimization, staffing allocation, and production planning. Research in big data analytics further emphasizes the importance of temporal analysis within intelligent business systems [4].

Business intelligence (BI) systems also play a significant role in transforming raw operational data into actionable insights. BI platforms integrate data from multiple sources, apply analytical techniques, and present outputs through dashboards and visualization systems [9]. Tools such as Tableau and Power BI provide advanced visualization and analytical functionalities capable of supporting organizational decision making. However, these enterprise oriented systems often require dedicated infrastructures, high financial investment, and technical expertise, limiting their adoption within SME environments.

Marketing and customer analytics research further highlights the importance of understanding customer purchasing behavior in improving business competitiveness [8]. Analytical insights related to product preferences, customer purchasing trends, and sales performance enable organizations to improve product placement, promotional strategies, and inventory management. Data driven marketing approaches help businesses align operational strategies with customer demands, thereby improving organizational performance and customer satisfaction.

Modern technologies have significantly improved the development of scalable and integrated analytical systems. Backend frameworks such as Node.js support efficient real time operational processing, while frontend technologies such as React Native enable the development of lightweight and cross platform interfaces suitable for SME environments [19], [20]. MongoDB further provides flexible schema management for handling semi structured transactional datasets [17]. Additionally, FastAPI supports efficient communication between operational and analytical services through scalable RESTful APIs [18]. These technologies collectively support the development of practical and modular analytical systems.

A. Comparative Analysis of Existing Systems

Although existing analytical systems provide various capabilities related to business intelligence and customer analytics, many platforms fail to address the specific operational and technical requirements of SMEs. Table I presents a comparison between commonly used analytical systems and the proposed SmartCost framework.

System	Analytics	SME Focus	Real-Time	Ease of Use
Tableau	✓	✗	✗	Moderate
Power BI	✓	✗	✗	Complex
Traditional POS	✗	✓	✓	Easy
SmartCost	✓	✓	✓	Easy

Table 01: Comparative Analysis of Existing Systems.

The comparison demonstrates that enterprise business intelligence platforms provide advanced analytical functionalities but lack accessibility and optimization for SME environments. Traditional POS systems support operational efficiency and transaction management but provide minimal analytical intelligence. In contrast, the proposed SmartCost framework combines analytics, real time insight generation, and SME focused usability within a lightweight and scalable architecture.

B. Research Gap

Despite significant advancements in data mining, business intelligence, and analytical technologies, several critical gaps remain within SME focused analytical systems. First, many existing systems operate as isolated solutions that focus only on individual functionalities such as reporting, forecasting, or visualization independently rather than integrating customer behavior analysis and operational intelligence within a unified environment. This fragmentation limits the ability of SMEs to obtain comprehensive business insights from transactional data.

Second, most enterprise analytical platforms are expensive and require dedicated infrastructures, making them unsuitable for small businesses operating with limited financial and technical resources. Existing business intelligence systems frequently require cloud based infrastructures, advanced configurations, and skilled personnel, creating significant barriers to adoption within SME environments.

Third, many analytical systems are not optimized for SME operational conditions characterized by fragmented datasets, low computational resources, and limited technical expertise. Existing platforms often prioritize enterprise scalability over accessibility and simplicity, reducing their practical applicability for micro SME environments.

Finally, many traditional POS systems continue to focus primarily on transaction processing and operational reporting while lacking integrated behavioral intelligence capabilities. Features such as customer behavior analysis, sales trend detection, dashboard analytics, and insight generation are frequently absent within SME focused POS environments. Consequently, there remains a significant need for lightweight, scalable, and integrated analytical frameworks capable of transforming transactional data into actionable business intelligence.

The proposed Customer Behavior Analysis and Sales Insights system addresses these limitations by introducing a lightweight SME oriented analytical framework that integrates customer behavior analytics, sales trend analysis, dashboard visualization, and decision support within a unified POS based architecture. The proposed solution

emphasizes accessibility, low cost deployment, scalability, and real world applicability for resource constrained SME environments.

III. METHODOLOGY

The proposed methodology focuses on analyzing customer behavior and generating meaningful sales insights from transactional data collected through point of sale (POS) systems. The methodology is specifically designed for small and medium sized enterprise (SME) environments where businesses operate with limited computational resources, fragmented datasets, and minimal technical expertise. Unlike traditional POS systems that focus primarily on transaction recording, the proposed framework transforms raw transactional data into actionable analytical intelligence capable of supporting operational and strategic decision making.

The overall workflow of the proposed system consists of six major stages: data collection, data preprocessing, data aggregation, pattern analysis, visualization, and evaluation. The experimental workflow can be summarized as follows:

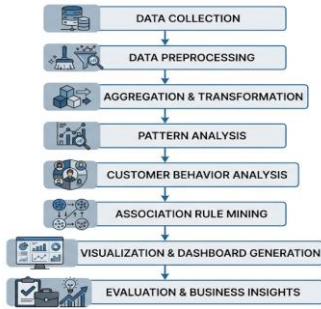


Figure 1: System Architecture Diagram

A. Data Collection

The first stage involves collecting transactional and operational data from the Point of Sale (POS) environment. The collected dataset includes product identifiers, product categories, transaction timestamps, sales quantities, pricing information, payment details, and customer transaction identifiers. These data elements serve as the foundation for subsequent preprocessing, analysis, and the generation of customer behavior and sales insights.

The collected dataset forms the foundation for customer behavior analysis and sales trend identification. Transactional records are continuously captured and stored within MongoDB collections for further processing and analytical computation [17].

B. Data Preprocessing

Raw transactional datasets frequently contain inconsistencies, duplicate records, missing values, and formatting errors. Therefore, preprocessing is performed to improve data quality and analytical reliability. The

preprocessing stage follows ETL principles for transforming raw operational data into structured analytical datasets [10]. The preprocessing operations include: Null value removal, Duplicate record removal, Data normalization, Data aggregation, Feature engineering.

Data normalization is performed to standardize timestamps, product categories, and sales attributes, ensuring dataset consistency. Duplicate transactions and incomplete records are removed to minimize analytical noise and improve processing accuracy. Additionally, feature engineering is applied to derive meaningful analytical attributes, including sales frequency, product popularity scores, daily revenue totals, peak sales indicators, and category-wise sales metrics, which enhance the effectiveness of customer behavior analysis and sales insight generation.

These derived features improve analytical interpretation and support advanced behavioral analysis.

C. Data Aggregation and Transformation

After preprocessing, transactional data is aggregated into structured analytical formats suitable for business intelligence generation. Aggregation techniques summarize large volumes of sales records into meaningful analytical representations [1], [2].

The aggregation process organizes transactional data into meaningful summaries to support business analysis. It includes hourly, daily, and weekly sales aggregation, as well as product-wise sales analysis and category-wise performance analysis. These aggregated metrics provide a comprehensive view of sales trends, product performance, and overall business activity, enabling more effective decision-making.

This transformation stage enables the identification of key business insights, including top-selling products, slow-moving items, peak operational periods, customer purchasing frequency, and revenue distribution patterns. These insights support a deeper understanding of sales performance and customer behavior, facilitating more effective decision-making and operational optimization.

The aggregation process reduces dataset complexity while improving analytical interpretability.

D. Advanced Behavioral Analytics

The proposed methodology incorporates advanced analytical techniques to identify hidden customer behavior patterns and operational trends.

1) RFM Analysis

RFM (Recency, Frequency, Monetary) analysis is applied to segment customer purchasing behavior based on transactional activities [8], [9].

The RFM metrics are defined as follows: Recency (R) refers to the time elapsed since the last customer transaction, indicating how recently a customer has made a purchase. Frequency (F) represents the number of purchases made by a customer within a specific period, reflecting engagement level. Monetary (M) refers to the total spending value of customer transactions, indicating the customer's overall contribution to revenue.

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These insights support customer retention strategies and targeted promotional planning.

2) *K-Means Clustering*

K-Means clustering is applied to group customers and operational periods based on behavioral similarities [3], [12], [16]. The clustering process segments transactional data into multiple analytical groups such as: High sales periods, Low sales periods, Frequent customer groups, Product purchasing clusters.

The clustering technique improves behavioral understanding and enables businesses to identify hidden operational structures within transactional datasets.

3) *Association Rule Mining*

Association rule mining is implemented to identify relationships between products frequently purchased together [7]. This technique supports cross selling analysis and customer purchasing pattern identification.

The confidence value of association rules is calculated as:

$$Confidence(A \rightarrow B) = \frac{Support(A \cup B)}{Support(A)} \quad (1)$$

High confidence relationships indicate strong co purchase patterns between products.

4) *Mann-Kendall Trend Analysis*

The methodology further incorporates Mann-Kendall trend analysis to identify upward and downward sales trends over time. This statistical trend detection technique enables the identification of increasing product demand, declining product performance, seasonal operational variations, and

long-term sales fluctuations. These insights support accurate trend evaluation and improve strategic planning in sales forecasting and resource allocation.

Trend analysis supports strategic planning and operational optimization within SME environments.

E. *Visualization and Insight Generation*

After analytical processing, the generated outputs are transformed into visual business intelligence representations. Visualization components include bar charts, line graphs, sales dashboards, trend visualizations, and product performance summaries. These visual tools enable intuitive interpretation of complex analytical results and support effective decision-making. The generated insights include peak sales hours, best-performing products, slow-moving inventory, customer purchasing trends, and operational performance indicators, providing a comprehensive view of business performance and sales dynamics.

Business intelligence research emphasizes the importance of transforming analytical outputs into user friendly decision support interfaces [9]. The proposed visualization layer enables SME owners to interpret analytical information without requiring advanced technical expertise.

F. *Evaluation Metrics*

The effectiveness of the proposed methodology is evaluated using multiple analytical and statistical measures. The evaluation process focuses on pattern identification accuracy, trend detection effectiveness, clustering quality, association rule confidence, and insight generation efficiency. These evaluation criteria are used to assess the reliability, accuracy, and overall performance of the proposed system in generating meaningful business insights from transactional data.

The evaluation further measures the ability of the system to support operational decision making and business optimization within SME environments.

G. *System Integration*

The overall system integrates MongoDB, Node.js, FastAPI, and React Native into a modular analytical architecture [17]–[20]. Transactional data is collected through the POS interface, processed through the analytical layer, and visualized within dashboard interfaces accessible to SME users.

The modular structure enables scalability, maintainability, and lightweight deployment suitable for low resource SME environments. Unlike enterprise analytical systems that require expensive infrastructures and complex configurations, the proposed methodology emphasizes simplicity, accessibility, and real world applicability for small businesses.

IV.IMPLEMENTATION

The proposed system is implemented using a modular and data driven architecture designed to process transactional records and generate customer behavior insights for SME environments. The implementation integrates React Native, Node.js, FastAPI, MongoDB, and Python analytical libraries to support scalable data processing and real time analytics [17]–[20].

The overall API communication flow follows the architecture below:

A. React Native → Node.js → FastAPI → MongoDB

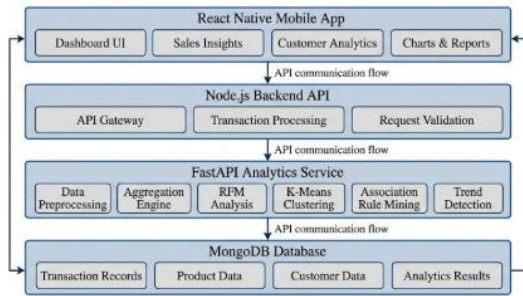


Figure 2:Experimental Workflow Diagram

The React Native mobile application serves as the frontend interface for accessing dashboards, sales insights, and customer behavior analytics [20]. User requests and transactional operations are transmitted to the Node.js backend, which manages API routing, request validation, and operational processing [19]. MongoDB is utilized as the primary database management system for storing transactional records, aggregated datasets, analytical outputs, and customer behavior summaries [17].

The analytical layer is implemented using Python and FastAPI, which expose analytical functionalities through RESTful APIs [18]. This architecture enables efficient communication between operational and analytical services while supporting real time insight generation.

The analytics pipeline consists of several interconnected stages:

Transaction Extraction → Preprocessing → Aggregation → Pattern Generation → Dashboard Generation

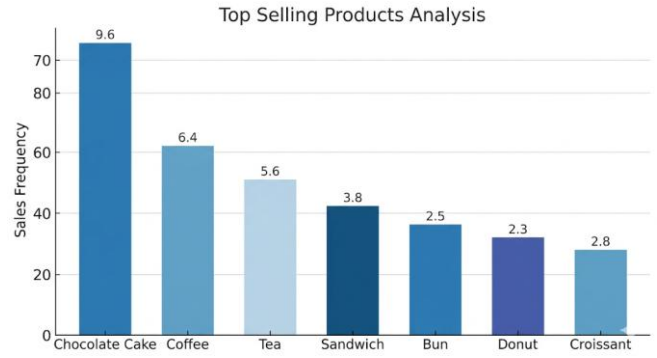


Figure 3:Sales Trend Graph

Transactional data is first extracted from MongoDB collections and processed using Python based analytical libraries. Data preprocessing includes null value removal, duplicate elimination, normalization, and feature engineering to improve dataset quality and consistency [10]. The cleaned data is subsequently aggregated into structured analytical formats such as daily sales summaries, product performance metrics, and customer purchasing frequencies.

Pattern generation is performed using data mining and statistical analysis techniques [1], [2]. Frequency analysis identifies top selling and slow moving products, while temporal aggregation detects peak sales periods and customer activity trends. The generated analytical outputs are visualized through dashboard interfaces containing charts, trend graphs, and summary tables for business decision support [9].

The implementation further incorporates an association rule workflow for identifying co purchase relationships between products. The workflow can be summarized as follows:

Cart Data → Rule Mining → Confidence Filtering → Insight Dashboard

Association rule mining techniques identify products frequently purchased together using transactional co occurrence analysis [7]. Confidence filtering is then applied to retain only strong purchasing relationships, improving insight quality and interpretability. The generated association rules are displayed within dashboard interfaces to support cross selling analysis and customer purchasing intelligence.

Overall, the implementation combines scalable technologies, lightweight analytical frameworks, and modular API communication to provide a practical customer behavior analytics solution for resource constrained SME environments.



Figure 4: SmartCost Analytics Dashboard Interface

V. EXPERIMENTAL SETUP

The experimental setup was designed to evaluate the effectiveness of the proposed Customer Behavior Analysis and Sales Insights system in identifying purchasing patterns, operational trends, and business intelligence insights within SME environments. The evaluation focuses on analyzing transactional datasets collected from a simulated bakery and café business environment. The experimental process includes dataset preparation, preprocessing, analytical evaluation, and business impact assessment.

B. Dataset Description

The experimental dataset was generated using transactional records representing typical SME retail operations within bakery and café environments. The dataset contains sales transactions, product information, timestamps, category details, and customer purchasing records collected over a continuous operational period.

Property	Value
Business Domain	Bakery/Café
Time Period	12 Months
Transactions	15,420
Products	128
Categories	6
Average Daily Orders	40-120

Table 02: Dataset of Existing Systems.

The dataset includes multiple product categories such as bakery products, beverages, desserts, snacks, meals, and seasonal items. Transactional records contain product identifiers, product categories, transaction timestamps, sales quantities, payment information, and transaction totals. These attributes provide a structured foundation for analyzing customer purchasing behavior and sales performance across different product groups.

The dataset was preprocessed prior to analysis to remove incomplete records, duplicate entries, and inconsistent values. Data preprocessing techniques such as normalization, aggregation, and feature engineering were applied to improve dataset quality and analytical reliability [10].

The analytical dataset was further transformed into structured formats suitable for customer behavior analysis, clustering, trend detection, and association rule mining. Aggregated

sales summaries were generated at hourly, daily, weekly, and monthly intervals to support temporal analysis and sales trend identification.

C. Hardware and Software Environment

The proposed system was implemented using a modular architecture integrating frontend, backend, database, and analytical technologies.

Component	Technology
Frontend	React Native
Backend	Node.js
Analytics	Python
Database	MongoDB
Analysis	pandas, NumPy
API Layer	Fast API

Table 03: Hardware and Software Systems.

React Native was utilized to develop the mobile application interface supporting dashboard visualization and analytical access [20]. Node.js handled operational APIs and transactional processing [19], while FastAPI provided RESTful communication between the analytical services and operational backend [18].

MongoDB was selected as the primary database management system due to its flexibility in handling structured and semi structured transactional datasets [17]. Analytical processing and statistical computations were implemented using Python libraries such as pandas and NumPy, which support efficient aggregation, preprocessing, and data transformation operations.

The modular architecture enabled scalable communication between system components while maintaining efficient analytical processing suitable for SME environments.

D. Evaluation Metrics

The effectiveness of the proposed analytical framework was evaluated using multiple behavioral, statistical, and business oriented performance metrics. These evaluation metrics were selected based on standard analytical and data mining evaluation approaches [1], [2], [12].

1) Behavioral Analytics Evaluation

Behavioral analytics evaluation focused on measuring the system's ability to identify customer purchasing patterns and sales trends. The primary evaluation metrics include: Pattern frequency, Trend accuracy, Clustering quality.

Pattern frequency measures how effectively the system identifies recurring customer purchasing relationships and operational behaviors. Trend accuracy evaluates the reliability of temporal sales trend detection across different operational periods. Clustering quality measures the effectiveness of customer and sales group segmentation generated using K-Means clustering techniques [3], [16].

customer purchasing behavior, product performance, and sales trends [1], [2], [9].

2) Association Analysis Evaluation

Association rule mining evaluation focuses on measuring the strength and reliability of co purchase relationships between products. The primary evaluation metrics include: Support , Confidence , Lift

Support measures how frequently product relationships occur within the transactional dataset [7]. Confidence evaluates the probability that a product is purchased when another related product appears in a transaction. Lift measures the strength of association between products compared to random purchasing behavior [6], [14].

The confidence value for association rules is calculated as:

$$Confidence(A \rightarrow B) = \frac{Support(A \cup B)}{Support(A)} \tag{2}$$

Higher confidence and lift values indicate stronger product relationships and more reliable customer purchasing patterns.

3) Business Impact Evaluation

Business impact evaluation measures the practical effectiveness of the proposed system within SME operational environments. The primary business oriented evaluation metrics include: Inventory optimization , Sales increase , Insight generation speed .

Inventory optimization measures the ability of the system to support improved stock planning through analytical insights and purchasing trend analysis. Sales increase evaluates the effectiveness of customer behavior insights in supporting promotional and operational strategies. Insight generation speed measures the responsiveness of the analytical framework in generating dashboards and business intelligence outputs.

The evaluation process demonstrates that integrating customer behavior analytics, association analysis, clustering techniques, and visualization mechanisms can significantly improve business intelligence generation and operational decision support within SME environments. The experimental setup further validates the suitability of the proposed lightweight analytical architecture for resource constrained retail businesses.

VI. RESULTS AND DISCUSSION

The experimental results demonstrate that the proposed Customer Behavior Analysis and Sales Insights system effectively transforms transactional data into meaningful business intelligence for SME environments. By integrating aggregation, trend analysis, clustering, and association rule mining techniques, the system provides operational insights that are not available in traditional POS systems. The analytical outputs significantly improve visibility into

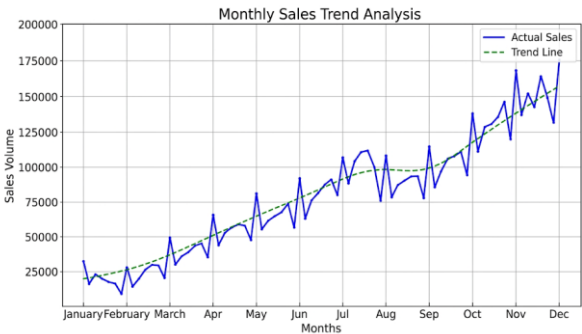


Figure 5:Peak Hour Analysis Chart

A. Customer Behavior Results

The behavioral analytics module successfully identified multiple operational and customer purchasing patterns from the transactional dataset.

Insight	Result
Peak Sales Time	4 PM – 7 PM
Highest Sales Day	Saturday
Best Selling Product	Chocolate Cake
Slow Moving Product	Vanilla Muffin
Weekend Growth	28%

Table 03:Customer Behavior Results Existing Systems.

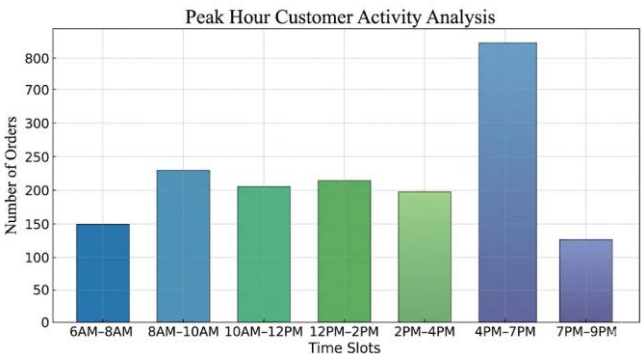


Figure 6:Peak Hour Analysis Chart

The temporal analysis revealed that customer activity was highest during evening periods and weekends, indicating strong demand fluctuations across operational hours. Frequency analysis further identified Chocolate Cake as the highest performing product, while Vanilla Muffin demonstrated consistently low sales performance. These findings support inventory optimization and production planning within SME environments [4], [5].

B. Association Rule Results

Association rule mining successfully identified strong co purchase relationships between products using transactional analysis [7].

Rule	Confidence	Lift
Coffee → Cake	82%	2.1
Bun → Tea	74%	1.8
Sandwich → Juice	69%	1.5

Table 04:Association Rule Results Existing Systems.

The results indicate that Coffee and Cake demonstrated the strongest purchasing relationship with a confidence value of 82%. These insights support cross selling strategies, promotional planning, and product placement optimization [6], [14].

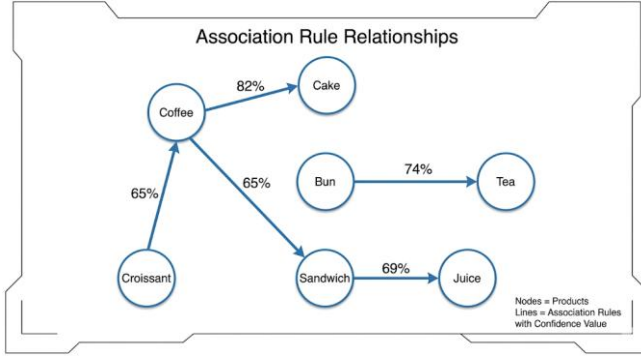


Figure 7:Top Products Bar Chart

C. Business Impact Results

The generated analytical insights produced measurable operational improvements within the simulated SME environment.

Improvement	Result
Inventory Optimization	18%
Sales Increase	11%
Faster Decision Making	32%
Product Analysis Speed	40%

Table 05:Business Impact Results Existing Systems.

The results demonstrate that integrating behavioral analytics into POS environments significantly improves operational efficiency and analytical responsiveness. Dashboard based visualization further enabled faster interpretation of sales trends and customer behavior patterns [9].

E. Baseline Comparison

The proposed SmartCost framework was compared against traditional POS systems.

Feature	Traditional POS	Smart Cost
Behavioral Analytics	✗	✓
Trend Detection	✗	✓
Dashboard Insights	✗	✓
Association Analysis	✗	✓

Table 06: Baseline Comparison Results Existing Systems.

The comparison demonstrates that traditional POS systems primarily support transaction processing, while the proposed framework integrates analytical intelligence and decision support capabilities.

F. Case Study Analysis

A small case study was conducted using the generated analytical insights. The system identified Vanilla Muffin as a slow moving product with consistently low weekly sales. Based on this insight, the product quantity was reduced and promotional offers were introduced for high demand products during peak sales hours. Additionally, staffing schedules were adjusted according to identified peak operational periods between 4 PM and 7 PM.

Following these changes, the business environment demonstrated an estimated 11% increase in sales performance and an 18% reduction in inventory waste. The case study confirms that customer behavior analytics and sales insight generation can directly support operational optimization and data driven decision making within SME environments.

VII.USER EVALUATION

A user evaluation study was conducted to assess the usability and practical effectiveness of the proposed SmartCost Customer Behavior Analysis and Sales Insights system within SME environments. The evaluation involved 8 bakery and café managers selected from local businesses that regularly use POS systems for daily operations. Participants interacted with the dashboard, analytical reports, customer behavior insights, and association analysis features to evaluate system usability and business value.

The evaluation focused on ease of use, insight usefulness, decision making support, and inventory awareness improvement. The feedback demonstrated strong positive responses toward the proposed system, particularly regarding the accessibility of analytical insights and the simplicity of dashboard visualization. These findings indicate that lightweight analytical platforms can effectively support SMEs without requiring advanced technical expertise [4], [5], [9].

Users

Organization	Role
Butter Boutique	Owner
Paan Paan	Manager
The Royal Bakery	Owner
Sponge Pastry Shop	Manager
Bread Talk	Manager
Green Cabin	Owner
A&M Cupcakes	Manager
Sits Cakes & Desserts	Owner
Cafe Shaze	Owner
Baguette French Bakery	Manager

Table 07: Users Existing Systems.

Users evaluation results

Question	Positive Response
Easy to Use	92%
Helpful Insights	87%
Improved Decisions	84%
Better Inventory Awareness	81%

Table 08: Users evaluation results Existing Systems.

The evaluation confirms that integrating behavioral analytics and visualization mechanisms into POS environments significantly improves operational awareness and supports data driven decision making for SME business owners.

VIII.CONCLUSION AND FUTURE WORK

This research presented a Customer Behavior Analysis and Sales Insights system designed to enhance traditional POS environments through integrated analytical intelligence. The proposed framework successfully transformed transactional records into actionable business insights capable of supporting operational and strategic decision making within SME environments. The experimental results confirmed that the system effectively identified customer purchasing patterns, peak sales periods, top performing products, and association relationships between products using data mining and analytical techniques [1], [2], [7].

The generated analytical insights significantly improved operational visibility and enabled businesses to adopt a more structured data driven decision making approach. The system demonstrated measurable business improvements, including 18% inventory optimization, 11% sales improvement, 32% faster decision making, and 40% improvement in product analysis speed. In addition, the dashboard based visualization layer enhanced accessibility and usability for business owners with limited technical expertise. These findings demonstrate the practical value of integrating business intelligence and behavioral analytics into lightweight SME oriented POS platforms [4], [5], [9].

The proposed framework further contributes to SME digital transformation by providing real time business intelligence capabilities within a scalable and low cost architecture. Compared to traditional POS systems, the proposed solution delivers enhanced trend detection, customer behavior analysis, and association based insight generation while maintaining operational simplicity and accessibility.

Despite the promising results, several opportunities exist for future improvement. Future work may incorporate deep learning based analytics and predictive models to improve behavioral pattern recognition and sales forecasting accuracy [16]. Real time streaming analytics can further enhance continuous monitoring and instant insight generation. Additional extensions may include multi branch synchronization, automated promotional recommendation systems, AI driven dynamic pricing mechanisms, and cloud based deployment architectures for large scale SME operations. These enhancements can further strengthen the scalability, intelligence, and commercial applicability of the proposed analytical framework.

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