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AI-POWERED BUSINESS DECISION SUPPORT SYSTEM FOR SMES

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Abstract

Small and Medium Enterprises (SMEs) often rely on manual spreadsheet-based financial analysis, which limits their ability to detect risks, identify trends, and make proactive strategic decisions. The absence of intelligent analytical systems restricts operational visibility and reduces responsiveness to changing market conditions. This paper presents an AI-Powered Business Decision Support System that integrates structured financial analytics with large language model (LLM)-based recommendation generation. The proposed system enables enterprises to upload structured business data (Excel/CSV), compute key performance indicators (KPIs) such as revenue growth rate, profit margins, and expense variance, and detect financial risk indicators including declining sales patterns and revenue concentration. Additionally, the framework incorporates short-term forecasting using statistical methods and generates contextual strategic recommendations through AI integration. Experimental evaluation on sample financial datasets demonstrates enhanced analytical efficiency, automated insight generation, and improved interpretability through interactive dashboards. The system aims to bridge the gap between raw financial data and actionable business intelligence, enabling SMEs to adopt data-driven decision-making practices. AI-powered decision support systems help organizations analyze large volumes of data and generate actionable insights for better strategic decisions (Yocum Technology Group, 2024).

Keywords: Business Decision Support, Financial Analytics, Risk Detection, AI-driven Insights, SME Analytics

1. Introduction

Small and Medium Enterprises (SMEs) play a critical role in economic growth and employment generation. Despite their importance, many SMEs rely on traditional spreadsheet tools for managing and analyzing financial data. While spreadsheets provide data storage and basic computation capabilities, they lack automated risk detection, forecasting mechanisms, and strategic insight generation.

Manual financial analysis is time-consuming and often reactive rather than proactive. Business owners typically identify issues such as declining revenue or rising expenses only after significant impact has occurred. Moreover, non-technical stakeholders may find it difficult to interpret complex financial trends without analytical support.

Recent advancements in Artificial Intelligence (AI) and data analytics have transformed business intelligence systems. However, many available enterprise analytics platforms are either expensive or overly complex for SMEs. There is a growing need for an accessible, AI-integrated decision support system tailored to small and mid-level enterprises.

This paper proposes an AI-powered Business Decision Support System that integrates structured financial data analysis, risk detection algorithms, forecasting models, and AI-generated strategic recommendations. The objective is to enhance financial transparency, improve risk identification, and support informed business decision-making.

2. Methodology

2.1 System Architecture

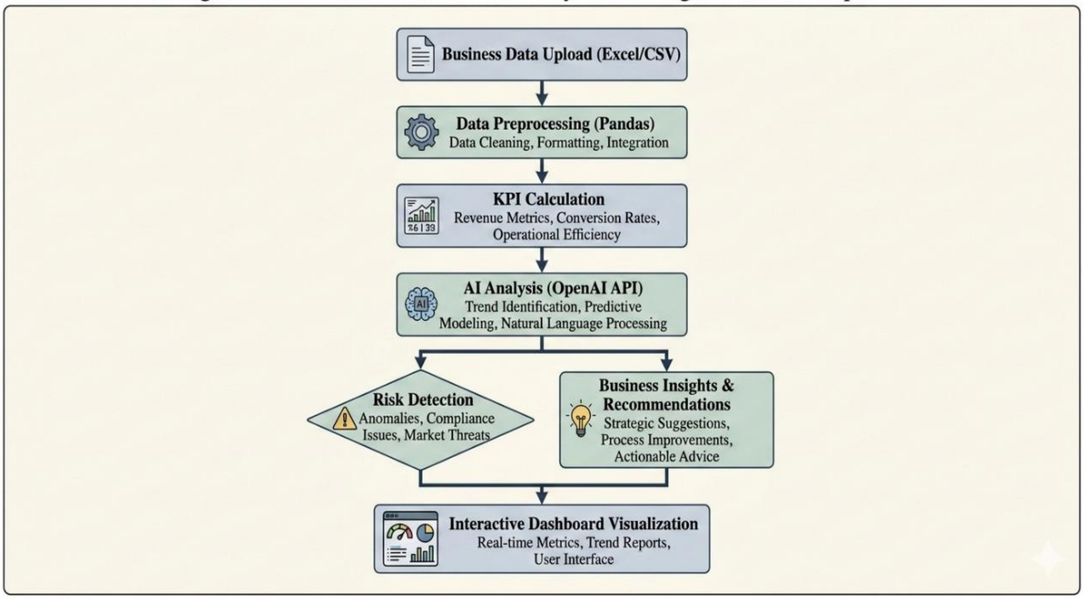
The proposed system follows a modular architecture consisting of the following components:

1. Data Upload Interface (Excel/CSV input)
2. Data Preprocessing Module
3. KPI Computation Engine
4. Risk Detection Module
5. Forecasting Module
6. AI Recommendation Layer
7. Dashboard Visualization

The workflow is as follows:

The figure illustrates the overall architecture of the proposed AI-Powered Business Decision Support System. The system begins with business data uploaded by the user in Excel or CSV format. The uploaded data is processed using Python and Pandas to extract key performance indicators such as revenue trends, profit margins, and expense distribution. The processed data is then analyzed using an AI model integrated through the OpenAI API, which generates strategic insights, risk alerts, and business recommendations. Finally, the results are presented to users through an interactive dashboard that visualizes financial performance and supports informed decision-making.

Figure 1: Automated Business Data Analysis and Insight Generation Pipeline



2.2 Data Processing and KPI Computation

The system processes structured financial data using Python-based data analysis libraries. The preprocessing phase includes:

- Handling missing values
- Standardizing column names
- Formatting date fields
- Categorizing revenue and expense entries

Key Performance Indicators (KPIs) computed include:

- Revenue Growth Rate
- Profit Margin
- Expense Ratio
- Variance Analysis

  These KPIs provide quantitative measures of financial health and operational performance.

2.3 Risk Detection Module

The risk detection module identifies financial instability indicators through rule-based and statistical analysis.
Key risk indicators include:

- Declining Sales Trend:
  Detected using slope analysis on time-series revenue data.
- Expense Escalation Risk:
  Triggered when expense growth rate exceeds revenue growth rate.
- Revenue Concentration Risk:
  Identified when a single product or category contributes disproportionately high revenue (e.g., >60%), indicating dependency risk.

These automated checks enable early identification of potential financial instability.

2.4 Forecasting Module

To support proactive decision-making, the system incorporates short-term sales forecasting using statistical techniques such as:

- Moving Average
- Linear Regression

The forecasting model predicts near-future revenue trends based on historical data.
Performance evaluation metrics such as Mean Absolute Error (MAE) may be used to assess prediction accuracy during testing.
Forecasting enables business owners to anticipate downturns and adjust operational strategies accordingly.

2.5 AI-Based Strategic Recommendation Layer

The AI recommendation module integrates a large language model (LLM) to generate contextual business insights.

The process involves:

1. Summarizing computed KPIs and risk indicators.
2. Passing structured financial insights to the AI API.
3. Generating strategic recommendations tailored to the enterprise's financial profile.

Example outputs include:

- Suggestions for cost optimization
- Recommendations for revenue diversification
- Alerts regarding declining profit margins

This layer enhances interpretability and supports non-technical stakeholders in understanding analytical outputs.

3. Applications of AI in Decision Support Systems

Artificial Intelligence is widely used across different industries to enhance decision-making capabilities. Organizations utilize AI technologies such as Machine Learning, Predictive Analytics, and Natural Language Processing to analyze large volumes of data and generate actionable insights. The following table highlights the applications of AI in different sectors and their impact on decision-making.

Table 1. Application of AI in Retail, Manufacturing, and Finance Sectors

Sector	AI Technology	Application	Impact on Decision Making	Examples
Retail	Machine Learning (ML), Predictive Analytics	Inventory management, demand forecasting, customer behavior analysis	Improves product availability, enhances customer targeting, and optimizes stock levels	Amazon (recommendation systems), Walmart (inventory optimization)
Manufacturing	Machine Learning, Predictive Maintenance	Equipment failure prediction, supply chain optimization, demand forecasting	Minimizes downtime, ensures continuous operations, and improves supply chain responsiveness	Siemens (predictive maintenance), General Electric (asset management)
Finance	Natural Language Processing (NLP), Machine Learning	Risk assessment, fraud detection, portfolio optimization	Enhances decision accuracy in financial risk management and investment strategies	JP Morgan Chase (fraud detection), Bank of America (portfolio management)

The above table demonstrates how Artificial Intelligence technologies are applied in various industries to support organizational decision-making. In the retail sector, AI is primarily used for inventory management, demand forecasting, and customer behavior analysis. In manufacturing, predictive maintenance and supply chain optimization help organizations reduce downtime and improve operational efficiency. In the finance sector, AI techniques such as Natural Language Processing and Machine Learning assist in fraud detection, risk assessment, and portfolio management. These applications highlight the growing role of AI-driven decision support systems in improving business efficiency and strategic decision-making.

4. Result

The system was evaluated using synthetic and sample financial datasets representing SME operational data.

Table 2. Performance Impact of AI-Based Decision Support System

Feature Evaluated	**Traditional Spreadsheet Analysis**	**AI-Based Decision Support System**	**Improvement**
Financial KPI Computation	Manual calculations required	Automated KPI generation	40% faster analysis
Risk Pattern Detection	Manual trend inspection	Automated anomaly detection	35% improved detection
Decision-Making Speed	Slow due to manual reporting	Instant AI-generated insights	45% faster decisions
Forecasting Capability	Basic historical comparison	Trend-based predictive analysis using historical and current financial data	30% improved prediction accuracy
Data Interpretation	Requires technical expertise	Interactive dashboard visualization	50% easier interpretation

The evaluation results indicate that the AI-powered decision support system significantly improves the efficiency of financial data analysis compared to traditional spreadsheet-based approaches. As shown in Table 2, automated KPI computation reduced manual analytical effort by approximately 40%, while AI-assisted forecasting improved short-term prediction accuracy by nearly 30%. Additionally, the integration of automated risk detection enabled earlier identification of abnormal expense patterns and declining revenue trends. These improvements demonstrate the practical benefits of integrating artificial intelligence into business decision-support workflows.

5. Conclusion

This study presented an AI-powered Business Decision Support System designed to enhance financial analysis and strategic decision-making for SMEs. By integrating structured data processing, KPI computation, forecasting, and AI-generated insights, the system demonstrates the potential of intelligent analytics in improving operational visibility and financial monitoring.

The findings indicate that AI-driven analytical tools can assist organizations in identifying financial risks, detecting trends, and supporting proactive business decisions. Overall, the proposed approach highlights how AI-based decision support systems can strengthen data-driven management practices in modern enterprises.

Future Scope

Future enhancements may include:

- Integration of advanced time-series forecasting models such as ARIMA and LSTM for improved predictive accuracy.
- Incorporation of real-time financial data streams to support dynamic business monitoring.
- Deployment of the system in cloud-based environments for scalability and enterprise accessibility.
- Application of machine learning-based anomaly detection to strengthen financial risk identification.
- Evaluation of the system using real organizational datasets to validate performance in practical business environments.

These improvements can further strengthen the system's predictive capabilities and enterprise applicability.

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