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BADSS - AI Powered Business Analytics and Decision Support System using Machine Learning

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Abstract

Business organizations generate large volumes of data every day from sales, customer records, inventory, and finance, yet many still rely on spreadsheets or reporting tools needing manual analysis and offering mainly historical information. This paper presents an AI powered Business Analytics and Decision Support System known as BADSS that automatically processes uploaded business data, computes key business indicators, forecasts future sales using Machine Learning, and generates recommendations using a Large Language Model. The proposed architecture introduces a layered control plane of data preprocessing, indicator computation, forecasting, an AI recommendation engine, and a reporting module, operating around a persistent knowledge base that retains historical analytics for future reference. The paper reviews related research on business intelligence, machine learning forecasting, and generative AI for enterprise decision support, identifies research gaps, and outlines an evaluation plan using representative business datasets. The proposed framework emphasizes automated insight generation, predictive accuracy, and faster decision making for modern organizations.

Keywords: Business Analytics; Machine Learning; Decision Support System; Sales Forecasting; Large Language Models

How to Cite This Article

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Introduction

Business organizations generate a large amount of data every day from sales, customer records, inventory, finance, and online transactions [2], [17]. This data contains valuable information that can help businesses improve their performance and make better decisions. However, many organizations still use spreadsheets or traditional reporting tools that require manual analysis and mainly provide historical information [2]. These methods are time consuming and do not help in predicting future business performance.

Artificial Intelligence (AI) and Machine Learning (ML), when combined with Business Intelligence (BI), enable soft-ware platforms to automatically process business data, identify patterns, and generate forward looking insight with minimal human involvement [13], [23]. As data volume and complexity grow, manual, spreadsheet driven analysis becomes increasingly time consuming, error prone, and unable to scale with the pace at which business conditions change. Moreover, the emergence of Large Language Models (LLMs) makes it possible to translate raw analytical output into clear, human readable recommendations, further lowering the barrier for non-technical decision makers [8], [21].

Businesses collect sales, customer, and operational data every day, but many organizations struggle to convert this data into useful decisions [2], [16]. Existing tools mainly show past performance through dashboards and reports, while managers still need to manually analyze data to understand problems like declining profits, low performing products, and changing customer demands [21].

Therefore, an intelligent analytics system is required that can automatically analyze business data, identify key fac-tors affecting performance, predict future sales, and provide recommendations to improve decision making [24], [25]. The challenge becomes more difficult when the system must handle unstructured, inconsistent, or incomplete data while remaining accessible and lightweight enough for adoption by organizations without dedicated data science teams. BADSS is proposed to address this gap through an integrated, closed loop analytics and recommendation pipeline.

Literature Review

Background and Definitions

Business Intelligence (BI) refers to the technologies, tools, and processes used to collect, integrate, analyze, and present business data to support decision making [2]. Business Analytics extends BI by applying statistical and machine learning techniques to historical data in order to identify trends and predict future outcomes [13].

A Decision Support System (DSS) is a software system that assists managers and business users in making decisions by analyzing large amounts of data and presenting actionable information [19]. When AI and ML are integrated into a DSS, the system gains the ability to learn from historical patterns, forecast future performance, and, increasingly, explain its findings and recommendations in natural language through generative AI and LLMs [8], [22].

Key Performance Indicators (KPIs) are quantifiable metrics, such as revenue, profit margin, and sales growth, used to evaluate business performance against strategic objectives [14]. In an AI powered analytics platform, KPI computation, predictive forecasting, and recommendation generation work together to shift organizations from a reactive, descriptive style of reporting toward a proactive, predictive, and prescriptive style of decision making [17], [20].

Related Work

Early and ongoing research on business intelligence establishes the idea that raw business data must be systematically transformed into actionable insight. Rothe and Shinde discuss how BI, when integrated with data science, converts large volumes of raw transactional and online data into meaningful insight, and argue that traditional analytical approaches are insufficient given the scale and complexity of modern business data [2]. Rane et al. review how AI and ML technologies, including predictive analytics, natural language processing, computer vision, and robotic process automation, are reshaping BI capabilities [13]. Paramesha et al. show how the convergence of Big Data, AI, IoT, and blockchain strengthens BI systems and improves the depth and timeliness of decision relevant insight [23]. Chen et al. performed a large-scale bibliographic study of BI and predictive analytics research published between 2000 and 2021, mapping historical trends and emerging research hotspots [17]. Antunes et al. examine how semantic web techniques can be embedded into data warehouse and BI systems to support strategic management decisions [5].

More recent studies focus specifically on the predictive component of business analytics platforms. Mustapha and Sithole apply machine learning models to forecast retail sales, demonstrating the practical value of predictive modeling for inventory and demand planning [6]. Biswas et al. propose an AI based sales forecasting model for digital marketing that extracts value from customer feedback to identify potential customers [15]. Khan et al. propose a demand forecasting model that combines BI with ML, reporting improved forecasting accuracy relative to conventional statistical methods [20]. Bergsma et al. present a systematic review of ML approaches applied to

inventory control optimization [9], while Mediavilla et al. review AI methods used for demand forecasting within supply chain management [18].

As predictive systems become more complex, explainability and generative AI have become central research concerns. Narlawar explores the integration of explainable AI (XAI) methods into enterprise analytics platforms, proposing a framework that balances technical performance with stake-holder trust [22]. Philip similarly evaluates how XAI enhances trust in management decision making [7]. Banh et al. investigate the use of generative AI in enterprise architecture, identifying affordances such as information synthesis and decision support content creation that closely parallel the LLM based recommendation capability used in BADSS [8]. Saidur evaluates AI enhanced BI dashboards for predictive market strategy, reporting measurable improvements in decision quality when generative and predictive AI capabilities are combined [21]. Domain specific studies, including customer behavior analysis in supermarket retail [11], churn prediction [12], sustainable KPI management in supply chains [14], and visual analytics for supply chain decision support [19], further confirm the practical value of AI/ML driven analytics but generally remain limited to a single operational domain rather than an integrated, general purpose platform. These insights motivate the BADSS design, which combines automated KPI computation, ML forecasting, and LLM based recommendation generation with operational traceability.

Summary of Reviewed Literature

Table 1 summarizes representative studies from the reviewed literature, highlighting the focus area, methodology, key contribution, and the research gap each study leaves open. These gaps collectively motivate the integrated, closed loop design adopted by BADSS.

Table 1. *Summary of Reviewed Literature on Business Intelligence, ML Forecasting, and AI Driven Decision Support*

Author (Year)	**Focus Area**	**Methodology**	**Key Contribution**	**Research Gap**
Rothe and Shinde (2026) [2]	Business Intelligence and data driven decisions	Conceptual review of BI and data science integration	Shows BI converts raw transactional data into meaningful insight	Lacks a concrete predictive or generative AI component
Rane et al. (2024) [13]	AI and ML in BI platforms	Survey of AI/ML techniques in BI platforms	Maps predictive analytics, NLP, and automation trends in BI	No unified architecture or evaluation plan proposed
Paramesha et al. (2024) [23]	Big Data, AI, IoT and blockchain convergence	Conceptual and literature-based analysis	Shows convergence of technologies strengthens BI depth	Does not address forecasting or recommendation generation
Chen et al. (2022) [17]	Bibliographic trends in BI and analytics	Bibliometric study, 2000 to 2021	Maps historical and emerging BI research hotspots	Descriptive only, no system design or implementation
Mustapha and Sithole (2024) [6]	Retail sales forecasting	Supervised ML regression models for demand planning	Demonstrates practical value of ML for demand planning	Limited to forecasting, no KPI or recommendation layer
Biswas et al. (2023) [15]	Digital marketing sales forecasting	AI based model using customer feedback data	Identifies potential customers from feedback signals	Domain specific to marketing, not general business use
Khan et al. (2020) [20]	Demand forecasting with BI and ML	Hybrid BI plus ML forecasting model	Reports improved accuracy over statistical baselines	No natural language explanation of forecasts
Bergsma et al. (2025) [9]	Inventory control optimization	Systematic review of ML approaches	Consolidates ML techniques for inventory decisions	Narrow focus on inventory, excludes broader KPIs
Narlawar (2025) [22]	Explainable AI in analytics	Framework proposal for XAI integration	Balances model performance with stakeholder trust	No forecasting or LLM recommendation integration
Banh et al. (2025) [8]	Generative AI in enterprise architecture	Affordance based qualitative analysis	Identifies synthesis and decision support affordances of generative AI	Not tied to a working analytics or forecasting pipeline

Saidur (2025) [21]	AI enhanced BI dashboards	Predictive plus generative AI dashboard evaluation	Reports improved decision quality with combined AI capabilities	Evaluation limited to dashboard perception, not end to end pipeline

Overall, the reviewed literature confirms strong individual progress in business intelligence, ML based forecasting, and explainable or generative AI, but most studies remain con-fined to a single capability or domain. Few works combine automated KPI computation, ML forecasting, and LLM based natural language recommendation within one closed loop, persistently traceable platform, which is the specific gap addressed by the proposed BADSS architecture.

Methodology

Proposed Architecture

The proposed BADSS architecture is organized into five logical layers that work together to provide continuous data ingestion, analytics, forecasting, recommendation generation, and persistent storage, as shown in Fig. 1.

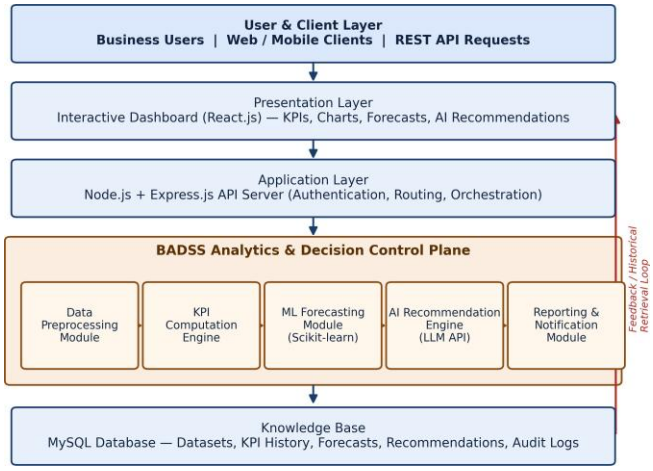


Fig 1. *System Architecture of Proposed BADSS platform*

1. User and Client Layer: This is the entry layer through which business users and external applications interact with the platform. Requests enter the system through standardized REST APIs, making integration easier for web and mobile clients. Users log in, upload business datasets, and view results through this layer.
2. Presentation Layer: The presentation layer hosts an interactive dashboard, built using React.js, which displays KPIs, charts, ML forecasts, and AI generated recommendations. This layer is kept responsive and user friendly so that non-technical business users can interpret results without additional training.
3. Application Layer: The application layer, implemented with Node.js and Express.js, handles authentication, request routing, and orchestration between the presentation layer and the analytics control plane. This modular structure improves maintainability and allows additional analytics modules to be added without redesigning the entire platform.
4. BADSS Analytics and Decision Control Plane: The control plane is the intelligence core of the system. It contains five functional modules that operate as a closed loop analytics pipeline:

- Data Preprocessing Module: Validates uploaded datasets, removes duplicate records, handles missing values, and converts data into a consistent format.
- KPI Computation Engine: Calculates core business KPIs such as total revenue, profit, profit margin, cost, sales growth, and top or least selling products.
- ML Forecasting Module: Applies machine learning models, for example regression and time series models built with Scikit learn, to predict future sales and business trends.
- AI Recommendation Engine: Sends analytics and fore-casting results to an LLM API, which generates easy to understand, actionable business recommendations.
- Reporting and Notification Module: Compiles results into reports and dashboards and can issue alerts through email or webhook channels.
- This layered design makes the system explainable and operationally manageable, and it is suitable for practical deployment because each module performs a clearly defined task.

5. Knowledge Base: The knowledge base is implemented as a persistent MySQL database that stores uploaded datasets, KPI history, forecasts, AI generated recommendations, and audit logs. This historical store allows the platform to retrieve past reports and supports future refinement of forecasting and recommendation quality, as indicated by the feedback loop in Fig. 1.

Methodology Workflow

The BADSS methodology follows an upload, preprocess, analyze, forecast, recommend cycle, illustrated as a closed loop in Fig. 2.

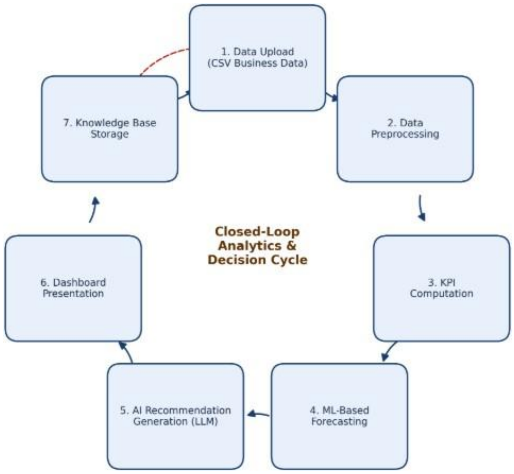


Fig 2. *Closed loop workflow for the BADSS methodology.*

The user first uploads a business dataset, typically in CSV format, containing sales, revenue, cost, product, and customer records. The preprocessing module then validates the dataset, removes duplicates, and handles missing values before the data is passed to the KPI computation engine, which calculates core business metrics and prepares them for visualization.

The ML forecasting module analyzes historical patterns in the cleaned data to predict future sales or revenue. The forecasting output, together with the computed KPIs, is passed to the AI recommendation engine, which uses an LLM to generate specific, actionable recommendations, for example, reducing discounts on low profit products, focusing on high performing products, or increasing inventory for products with growing demand. All results, along with the underlying dataset, are stored in the knowledge base, and the dashboard presents revenue, profit, profit margin, charts, ML predictions, and AI recommendations together so that business owners can make data driven decisions quickly.

The methodology is intentionally practical rather than overly complex. Instead of depending entirely on opaque end to end deep learning, it combines transparent KPI computation with supervised ML forecasting and LLM based explanation, making the system easier to validate in real deployments and suitable for student projects, prototype deployment, and incremental future enhancement.

Implementation Plan

The implementation can be prototyped using React.js for the frontend, Node.js with Express.js for the backend, Python (Pandas, NumPy, and Scikit learn) for analytics and machine learning, MySQL for persistent storage, an LLM API for recommendation generation, and Chart.js or Recharts for visualization.

1. Evaluation Scenarios: The evaluation should include at least the following scenarios:
   - Clean structured dataset: a well formatted business dataset with no missing values, used as a baseline case.
   - Dataset with missing or duplicate records: to test the robustness of the preprocessing module.
   - Seasonal sales dataset: to test the forecasting module's ability to capture cyclic demand patterns.
   - Sudden demand shift: a dataset with an abrupt change in sales trend, to test forecasting responsiveness.
   - Multi category product dataset: to test KPI computation and recommendation quality across several product lines simultaneously.
2. Metrics: The evaluation should measure:
   - Forecasting accuracy (e.g., Mean Absolute Error, Root Mean Squared Error).
   - KPI computation correctness against manually verified values.
   - Time taken from data upload to dashboard generation.
   - Relevance and clarity of AI generated recommendations, assessed through user feedback.
   - Dashboard responsiveness and system resource usage.
   - Robustness to missing, duplicate, or inconsistent data.

3. Baseline: The baseline should be a traditional, manual analysis workflow using spreadsheets and static reporting tools without ML forecasting or AI generated recommendations. BADSS should be compared against this baseline to show whether the automated pipeline improves analysis speed and decision quality. Even a small experimental setup with a handful of real or synthetic business datasets can demonstrate whether automated analytics reduces manual effort.
4. Expected Evaluation Outcome: The expected outcome is that BADSS will compute KPIs and generate forecasts significantly faster than manual analysis while maintaining acceptable forecasting accuracy. The system should also produce recommendations that business users find clear and actionable, and the knowledge base should allow consistent retrieval of historical analytics for comparison across reporting periods.

Conclusion

AI powered business analytics and decision support systems are increasingly essential for modern organizations because they reduce dependence on manual data analysis and support faster, more consistent decision making. The BADSS architecture presented in this paper provides a structured, closed loop framework for data preprocessing, KPI computation, ML based forecasting, AI generated recommendation, and persistent storage. Its layered design supports usability, transparent reporting, and historical traceability.

By combining a control plane, persistent knowledge base, and LLM based recommendation engine, the proposed model offers a practical foundation for building accessible, AI driven analytics platforms. Future work can extend the framework with real time data integration from ERP, CRM, and POS systems, improved prediction accuracy using deep learning and advanced forecasting models, role based dashboards for managers, sales teams, and executives, industry specific solutions for retail, healthcare, finance, and manufacturing, cloud deployment for secure and scalable multi location access, anomaly detection for early identification of business risks, and what if scenario analysis to support strategic planning. The result is a more adaptive and dependable analytics platform suited for real world business decision making.

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