# Transforming Forecasting for Local Business: Generative AI vs. Traditional Predictive Models

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## Executive Summary

The landscape of business forecasting is undergoing a significant transformation with the emergence of generative artificial intelligence (AI), presenting both opportunities and challenges for local businesses. This white paper provides a comprehensive analysis comparing traditional predictive models with generative AI approaches in business forecasting, particularly focusing on their applications, benefits, and limitations.

Traditional forecasting methods, including regression analysis, time series modeling, and exponential smoothing, have served as reliable tools for decades. These approaches excel in stable market conditions and provide transparent, interpretable results. However, they often struggle with complex, dynamic environments and unstructured data, limiting their effectiveness in today's rapidly evolving business landscape.

Generative AI represents a paradigm shift in forecasting capabilities. Through advanced technologies like Generative Adversarial Networks (GANs) and transformer models, it offers a superior ability to:

- Process and analyze diverse data sources simultaneously
- Adapt to real-time market changes
- Generate multiple scenario simulations
- Identify complex, non-linear patterns in data
- Provide more nuanced and accurate prediction

A detailed case study of a local restaurant demonstrates how generative AI can optimize operations by integrating multiple data streams to improve sales forecasting, inventory management, and staffing decisions. The implementation framework provided outlines a structured approach for businesses transitioning to AI-enhanced forecasting systems.

The adoption of generative AI comes with significant considerations, including data quality requirements, implementation costs, technical expertise needs, and change management challenges. For local businesses, the choice between traditional and AI-based forecasting methods should be based on their specific needs, resources, and technical readiness.

This analysis concludes that while generative AI offers transformative potential for business forecasting, a balanced approach considering both traditional and AI-based methods may be optimal for many local businesses. The white paper provides practical recommendations for businesses to evaluate and implement appropriate forecasting solutions while addressing potential challenges and risks.

The insights and frameworks presented in this white paper aim to help local business leaders make informed decisions about their forecasting strategies, ultimately enabling them to enhance operational efficiency and maintain competitive advantage in their respective markets.

*"...over 90% of business leaders believe that accurate forecasting is essential for strategic decision-making... Generative AI offers a more dynamic and nuanced approach to forecasting, introducing new possibilities and challenges"*

## Introduction

Forecasting plays a pivotal role in the success of local businesses (Nguyen, 2024). Accurate predictions enable better resource allocation, customer satisfaction, and financial stability (Ordu et al., 2021). Traditional predictive models have long been employed for forecasting, relying on historical data and statistical methods. However, the emergence of Generative AI offers a more dynamic and nuanced approach to forecasting, introducing new possibilities and challenges (Balasubramaniam et al., 2024).

The ability to predict future trends is critical for businesses to remain competitive and adaptive in today's fast-paced and data-driven economy. Traditionally, forecasting has relied on statistical models and historical data, using methods such as time series analysis and linear regression. While these techniques have provided a strong foundation, they often fall short in dynamic and uncertain environments where patterns are nonlinear, datasets are large or unstructured, and market conditions shift rapidly (Dallasega et al., 2021).

In the post-pandemic years, businesses are facing unprecedented levels of volatility and complexity, and the ability to forecast future trends has become more critical than ever. According to recent studies, over 90% of business leaders believe that accurate forecasting is essential for strategic decision-making (Ijaz, 2024), and traditional methods often fall short in addressing today's dynamic and nonlinear markets. From supply chain disruptions to rapidly changing consumer behaviors, organizations are constantly challenged to adapt and anticipate the unknown. The ability to predict future trends and outcomes is critical for businesses to remain competitive and adaptive in today's fast-paced and data-driven economy.

Traditionally, forecasting has relied on statistical models and historical data, using methods such as time series analysis and linear regression (Xu et al., 2019). While these techniques have provided a strong foundation, they often fall short in dynamic

and uncertain environments where patterns are nonlinear, datasets are large or unstructured, and market conditions shift rapidly. With businesses now operating in highly interconnected and fast-paced global markets, the inability of traditional models to adapt quickly to unexpected changes or integrate diverse data sources leaves organizations vulnerable to inaccurate forecasts and missed opportunities (Dallasega et al., 2021).

Generative AI, a cutting-edge advancement in artificial intelligence, refers to systems capable of generating new data that mimics patterns found in existing datasets, identifying hidden relationships, and generating realistic simulations of future scenarios. For example, models like Generative Adversarial Networks (GANs) can create synthetic sales data to simulate potential market outcomes, while Transformer-based models can analyze vast amounts of structured and unstructured information to predict emerging trends. This ability to process complex datasets, identify hidden relationships, and generate realistic simulations of future scenarios is transforming business forecasting.

Unlike traditional models, generative AI can adapt in real time, integrate multiple data sources, and provide forecasts that are both accurate and resilient to disruptions. This transformative potential positions generative AI as a game-changing technology for businesses seeking to enhance decision-making and gain a competitive advantage (Morales-García et al., 2024).

Local businesses often operate in dynamic environments, requiring forecasting models that adapt quickly and provide actionable insights. Historically, traditional predictive models, such as time-series analyses and regression methods, have served as reliable tools for forecasting. However, these methods often require substantial historical data to develop the model, and their performance can be limited in scenarios with rapid changes or sparse data. Additionally, Clarksville's rapid growth, fast changing market conditions, changing consumer behaviors, and increasing data complexity poses unprecedented challenges in local business forecasting.

Generative AI, powered by advancements in machine learning and deep learning, offers an alternative approach. By leveraging large datasets and using sophisticated tools like neural networks, support vector machines (SVM) etc., generative models can create synthetic data, simulate potential scenarios, and generate insights that go beyond conventional methods.

In this white paper, we attempt to explore how generative AI is reshaping forecasting methodologies and compare its effectiveness with traditional predictive models in the context of local business operations while empowering them to navigate through uncertainty with confidence. We also explore the transformation of forecasting practices for local businesses, contrasting the capabilities of Generative AI with those of traditional predictive models. By understanding their respective strengths and weaknesses, local businesses can harness the power of forecasting to thrive in competitive markets.

## The Evolution of Business Forecasting

### Early Foundations (Pre-1900s)

The foundations of forecasting can be traced to early civilizations' attempts to predict natural phenomena. Ancient Egyptians developed the Nilometer to forecast harvest yields based on river levels, while Chinese astronomers created complex celestial models to predict astronomical events. However, these methods relied heavily on observation and intuition rather than mathematical principles.

The emergence of probability theory in the 17th century, pioneered by Pascal and Fermat, laid the groundwork for modern forecasting. Bernoulli's work on the law of large numbers (1713) and Bayes' theorem (1763) provided the mathematical framework for understanding uncertainty in predictions.

### Classical Statistical Methods (1900-1960)

The early 20th century marked a significant shift toward systematic forecasting approaches:

### Regression Analysis

Regression analysis has been a fundamental tool in business forecasting, enabling organizations to predict trends, model relationships between variables, and make informed decisions. Its application spans across sales forecasting, market analysis, financial planning, and operations management. This literature review examines the role of regression analysis in business forecasting, highlighting its methodologies, applications, and advancements.

The use of regression analysis in business forecasting dates back to the early 20th century when statistical tools gained prominence in economic modeling. Tinbergen (1939) utilized regression techniques to analyze economic cycles, paving the way for their application in business contexts. Over time, the method evolved to incorporate more sophisticated approaches, such as multiple regression and time series regression, to handle complex business data.

Regression analysis involves modeling the relationship between a dependent variable (e.g., sales) and one or more independent variables (e.g., advertising expenditure, market trends). In business forecasting, the focus is often on identifying predictors that influence key performance metrics.

- **Linear Regression:** Assumes a linear relationship between variables.
- **Multiple Regression:** Includes multiple predictors to improve accuracy.
- **Logistic Regression:** Used for categorical outcomes, such as forecasting customer churn.
- **Time Series Regression:** Integrates temporal components to model trends and seasonality.

Applications of regression analysis in business forecasting include:

1. **Sales and Revenue Forecasting:** Regression models are widely used to forecast sales based on factors like historical sales data, pricing strategies, and promotional efforts (Armstrong, 2001). For example, multiple regression can model the effect of marketing spend and economic indicators on revenue.
2. **Market Demand Analysis:** Regression helps predict market demand by analyzing variables such as consumer behavior, demographic trends, and external factors like economic conditions (Kotler & Keller, 2016).
3. **Financial Forecasting:** In finance, regression models predict stock prices, interest rates, and risk assessment. Fama and French (1992) used regression to model asset returns based on factors like market size and book-to-market ratios.
4. **Operational Planning:** Regression analysis aids in demand planning and inventory management by forecasting product demand based on seasonality and historical usage patterns (Silver et al., 1998).

**Time Series Analysis**

Time series analysis emerged as a systematic approach to understanding patterns in sequential data. The foundational work of Yule (1927) introduced the concept of autoregression, while Wold's (1938) decomposition theorem provided the theoretical basis for modern time series analysis. Yule's (1927) introduction of autoregressive models represented a breakthrough in time series analysis. This was followed by Slutsky's (1937) moving average models, culminating in the development of Autoregressive Integrated Moving Average (ARIMA) models by Box and Jenkins in the late 1960s. Time series analysis typically examines four main components a) Trend: Long-term movement in the data; b) Seasonality: Regular, periodic fluctuations; c) Cyclical patterns: Irregular but recurring fluctuations; and d) Random variations: Unexplainable statistical noise.

Applications of time series analysis in business forecasting:

1. **Sales Forecasting:** Time series analysis is widely applied to predict sales trends and seasonality, helping businesses optimize inventory and pricing strategies (Makridakis et al., 1998). For instance, Holt-Winters models are used to forecast monthly sales patterns.
2. **Financial Forecasting:** In finance, time series models predict stock prices, interest rates, and currency exchange rates. GARCH models, for example, are used to forecast market volatility (Engle, 1982).
3. **Demand Planning:** Time series methods help businesses predict product demand, ensuring efficient supply chain management and reducing operational costs (Silver et al., 1998).
4. **Energy and Resource Forecasting:** Utility companies leverage time series analysis to forecast electricity and water consumption, enabling better resource allocation (Taylor, 2010).

**Moving Averages**

Among the other forecasting techniques, moving average methods was very popular due to their simplicity, robustness, and adaptability. The concept of moving averages traces back to the early 20th century, primarily in financial market analysis. Kendall and Hill (1953) were among the first to formalize moving averages in time series analysis, establishing their utility in smoothing volatile data. Since then, the methodology has evolved, with adaptations such as weighted moving averages (WMA) and exponential moving averages (EMA) addressing the limitations of simple moving averages (SMA).

Moving averages operate on the principle of smoothing past data to forecast future values. SMA calculates the unweighted mean of a fixed number of past observations, while WMA assigns greater weights to recent observations. EMA further refines this approach by applying exponential weighting, enabling faster adaptation to recent trends (Brown, 1959). These methods are particularly effective in reducing noise in time series data, making patterns more discernible.

Applications of moving averages in business:

1. **Financial Markets:** Moving averages are extensively used in technical analysis to identify trends and generate trading signals. Studies such as Brock, Lakonishok, and LeBaron (1992) demonstrated the effectiveness of SMA and EMA in predicting stock price movements.
2. **Supply Chain Management:** In inventory control and demand forecasting, moving averages help manage stock levels and reduce wastage. Silver, Pyke, and Peterson (1998) emphasized the role of weighted moving averages in achieving higher forecast accuracy in supply chain contexts.
3. **Meteorology:** Moving averages are applied to smooth weather data, facilitating accurate climate predictions. For instance, Jones et al. (2015) used moving average techniques to analyze long-term temperature trends.
4. **Macroeconomic Analysis:** Moving averages aid in smoothing economic indicators like GDP growth rates and inflation, offering insights into cyclical patterns (Hodrick & Prescott, 1997).

**Exponential Smoothing**

Brown (1956) and Holt (1957) developed exponential smoothing techniques, providing practical tools for business forecasting. Winters (1960) extended these methods to handle seasonal patterns, creating the Holt-Winters method still widely used today. Exponential smoothing is a widely used time series forecasting method due to its simplicity and effectiveness in capturing trends and seasonality. Unlike Autoregressive Integrated Moving Average (ARIMA) model of time series analysis, exponential smoothing places exponentially decreasing weights on past observations, making it highly adaptable for short-term forecasting. Key exponential smoothing methods:

1. **Single Exponential Smoothing:** Appropriate for data with no clear trend or seasonality, this method smooths data using a weighted average of past observations (Brown, 1959).
2. **Double Exponential Smoothing:** Also known as Holt's method, it extends single smoothing to account for trends in the data (Holt, 1957).
3. **Triple Exponential Smoothing:** Commonly referred to as the Holt-Winters method, this approach incorporates both trend and seasonality, making it ideal for business applications such as sales forecasting and inventory management (Winters, 1960).

Applications of exponential smoothing in business:

1. **Retail Sales:** Forecasting demand for seasonal products.
2. **Operations Management:** Inventory and workforce planning.
3. **Revenue Projections:** Predicting monthly or quarterly revenue streams.

These methods excel in stable environments with clear historical patterns but often struggle with rapid market changes and complex variables.

## Generative AI in Business Forecasting

Generative AI, driven by technologies like Generative Adversarial Networks (GANs) and large language models (LLMs), introduces a paradigm shift in forecasting. Unlike traditional forecasting methods, generative AI can process vast datasets from diverse sources, such as market trends, customer behavior, and external factors like weather or economic conditions, to provide actionable insights. Its ability to generate realistic "what-if" scenarios allow businesses to prepare for uncertainties, optimize resource allocation, and make proactive decisions. By continuously learning and adapting to real-time data from varied dimensions, generative AI ensures dynamic and precise forecasts, driving efficiency, reducing costs, and enhancing strategic planning across industries. Additionally, generative AI can create synthetic data, simulate scenarios, and provide context-aware predictions by leveraging vast datasets.

Generative AI leverages machine learning models like GANs, variational autoencoders, transformers etc. to simulate data distributions, generate synthetic data, and identify complex, nonlinear relationships. It processes large-scale, multidimensional, and unstructured datasets. Another important feature of generative AI - it is adaptive to changing environments and evolving trends and enhances accuracy through real-time learning and scenario simulations. However, implementation and interpretation of generative AI outcomes require expertise in AI and data science. Also, it requires significant computational resources and data availability.

### Advantages

1. **Dynamic Adaptability**: Generative AI can adapt to emerging trends and anomalies in real-time.
2. **Enhanced Accuracy**: By analyzing diverse datasets, Generative AI identifies intricate patterns and relationships.

3. **Scenario Simulation**: It allows businesses to generate multiple scenarios, enabling better contingency planning.
4. **Automation**: Reduces human intervention and accelerates forecasting processes.

## Real-World Applications and Case Study

### Demand Forecasting

- **Traditional Models**: Use historical sales data to predict future demand. Effective for businesses with stable, repetitive patterns.
- **Generative AI**: Incorporates external factors like weather, social media trends, and local events, providing more nuanced predictions.

### Inventory Management

- **Traditional Models**: Employ reorder point and safety stock calculations to manage inventory.
- **Generative AI**: Offers dynamic inventory optimization by simulating demand fluctuations and supplier disruptions.

### Customer Behavior Analysis

- **Traditional Models**: Segment customers based on demographic data and purchase history.
- **Generative AI**: Creates personalized insights by analyzing customer interactions, preferences, and sentiment.

### Case Study: Local restaurant's weekly sales and staffing

A mid-sized restaurant wants to improve weekly sales forecasting and optimize staffing schedules based on demand patterns. Currently they are using time series analysis for sales forecasting. If they want to adopt a more dynamic forecasting, generative AI will be immensely useful.

In that case, they need to follow these steps:

**Step 1: Data Collection and Integration**

The restaurant integrates its data sources with a generative AI model:

- Point of Sale (POS) Data: Historical sales data for menu items by day, week, and season.
- Customer Data: Information from loyalty programs and online reservations.
- External Factors: Weather conditions, local events, holidays, and economic trends.
- Operational Data: Employee schedules, food inventory, and operational costs.

**Step 2: Data Analysis and Forecasting**

The generative AI model processes this data to identify patterns and simulate future scenarios:

1. **Sales Predictions:** The AI uses historical sales data combined with upcoming weather forecasts and events to predict daily and weekly revenue. For instance, it predicts a spike in sales for outdoor dining due to sunny weather on the weekend or an uptick during a local festival.
2. **Customer Behavior Forecasting:** It analyzes reservation trends to estimate peak dining hours. Predicts which menu items will sell more based on historical popularity and seasonal preferences.
3. **Staffing Optimization:** The AI model suggests optimal staffing levels for each shift based on predicted customer volume, minimizing overstaffing or understaffing. For example, it recommends adding extra staff for a Friday evening with expected high footfall due to a nearby concert.

**Step 3: Inventory and Menu Adjustments**

The generative AI identifies trends to optimize inventory management and menu offerings:

- Ingredient Forecasting**:** Predicts demand for key ingredients to reduce waste and prevent shortages. Suggests placing a larger order for seafood if it detects a trend for seafood dishes in warm weather.
- Dynamic Menu Adjustments**:** Recommends promoting high-margin dishes or creating specials for items with excess inventory.

**Step 4: Scenario Simulation**

The generative AI generates "what-if" scenarios to prepare for unexpected changes:

- Simulates the impact of a sudden storm on outdoor seating sales.
- Models the effect of offering a 10% discount on a slow weekday to attract more customers.
- Predicts customer reactions to a new menu item launch.

**Step 5: Visualization and Insights**

The AI creates user-friendly dashboards and reports:

- Displays a heatmap of predicted sales by time, day and week (as required).
- Visualizes profit margins for different menu items.
- Offers actionable recommendations, such as "Hire two additional waitstaff for Friday evening" or "Run a social media ad campaign for brunch specials."

**Step 6: Continuous Learning**

The integration of Generative AI in business forecasting represents a transformative approach to predictive analytics, characterized by its ability to continuously learn and adapt to new data patterns. Unlike traditional forecasting models that remain static after initial training, generative AI systems can dynamically incorporate real-time market changes, consumer behavior shifts, and emerging economic indicators to refine their predictions. This continuous learning capability enables businesses to capture subtle market trends, seasonal variations, and unexpected disruptions, leading to more accurate and nuanced forecasts.

For instance, during supply chain disruptions or sudden market shifts, these systems can quickly adjust their predictions by recognizing new patterns in data streams, helping organizations make more informed decisions about inventory management, resource allocation, and strategic planning. The self-improving nature of these AI systems also means that their forecasting accuracy tends to increase over time as they accumulate more historical data and learn from their previous predictions' performance, ultimately providing businesses with a more robust and adaptable forecasting framework.

In this example, generative AI adapts to real-time changes, it refines its predictions based on daily sales data, weather updates, and customer feedback. Also, it suggests iterative improvements to staffing, inventory, and promotions over time.

See Diagram 1 for a visual representation of how generative AI enhances business forecasting for a restaurant.

**Implementation Framework**

The integration of generative AI into business forecasting requires a structured approach:

1. **Assessment:** Evaluate existing forecasting systems and identify pain points.

2. **Data Preparation:** Consolidate historical, real-time, and unstructured data for AI training.
3. **Model Selection:** Identify appropriate generative AI techniques based on business needs (e.g., GANs for scenario simulations, Transformer-based models for trend analysis).
4. **Pilot Testing:** Implement AI models on specific forecasting tasks to assess accuracy and adaptability.
5. **Deployment and Monitoring:** Scale AI models while ensuring continuous monitoring and model retraining.

**Potential Benefits**

- **Improved Accuracy:** Generative AI's ability to identify hidden trends and simulate multiple scenarios leads to more precise forecasts.
- **Enhanced Agility:** Real-time adaptability allows businesses to respond quickly to market changes.
- **Competitive Advantage:** Better forecasting enables optimized resource allocation, reduced costs, and increased profitability.
- **Decision Support:** Scenario simulations provide executives with robust insights for strategic planning.

## Challenges and Considerations

1. **Data Quality**: Both approaches require accurate and comprehensive data for effective forecasting. Local businesses must invest in robust data collection systems.
2. **Integration**: Adopting new technologies like Generative AI may require overhauling existing systems, posing logistical challenges.
3. **Cost-Benefit Analysis**: Businesses must weigh the benefits of improved forecasting accuracy against the costs of implementation.
4. **Ethical Implications**: Transparency, data privacy, and bias mitigation are critical

concerns when employing AI. Also, sometimes, use of proprietary or sensitive data raises ethical and legal issues. While generative AI offers substantial benefits, it is not without challenges such as:

**Data Dependency:** Generative AI relies heavily on data dependency to function effectively, as the quality and diversity of data directly influence the accuracy and reliability of its outputs. These models require large datasets to learn patterns, correlations, and distributions that enable them to generate realistic and relevant predictions or content. Data inputs must encompass a broad spectrum of variables, such as historical trends, user behaviors, external influences, and domain-specific nuances, ensuring the AI's adaptability and relevance. This dependency also highlights potential challenges, including biases in data, incomplete datasets, and the need for continuous updates to maintain accuracy. As a result, managing, curating, and validating data are critical aspects of deploying generative AI successfully, emphasizing the importance of robust data pipelines and governance practices.

**Resource Intensive:** Generative AI is inherently resource-intensive, requiring significant computational power, memory, and storage to train and deploy effectively. Training large-scale models involves processing massive datasets, often using high-performance GPUs or TPUs, which consume considerable energy and time. Even after training, real-time inference can be demanding, especially for applications involving complex simulations or high-volume queries. This resource intensity extends to data storage, as generative AI relies on vast amounts of high-quality data for optimal performance. Additionally, maintaining and fine-tuning these models demands skilled professionals, robust infrastructure, and financial investment. As a result, businesses leveraging generative AI must balance its transformative potential with the associated costs, exploring innovations like model optimization and cloud-based solutions to mitigate resource demands.

**Interpretability:** AI outputs may be less transparent compared to traditional methods. The interpretability of generative AI presents a significant challenge, as the inner workings of these models often function as "black boxes", making it difficult to understand how specific outputs are produced. These models, especially those based on deep learning, rely on intricate neural networks with millions or billions of parameters, which can obscure the logical connections between inputs and results. This lack of transparency can hinder trust and adoption in critical industries like healthcare, finance, and legal, where accountability and explainability are paramount. Furthermore, the inability to fully interpret decisions or predictions

complicates debugging and addressing biases embedded within the system. Addressing this challenge requires the development of explainable AI techniques, where models are designed to provide clear and human-readable justifications for their outputs, bridging the gap between accuracy and transparency.

**Change Management:** The implementation of generative AI poses significant change management challenges, as it requires businesses to adapt their workflows, culture, and mindset to leverage this transformative technology effectively. Employees may resist adopting AI-driven systems due to fear of redundancy or lack of understanding, necessitating comprehensive training and communication strategies to build trust and acceptance. Additionally, integrating generative AI into existing infrastructure often demands substantial reorganization, new investments, and alignment of teams across technical and operational domains. Businesses must also address ethical concerns, redefine roles, and establish clear governance frameworks to ensure the responsible use of AI. Successfully navigating these challenges requires a structured change management approach, fostering collaboration, providing education, and demonstrating the tangible benefits of generative AI to all stakeholders. Requires upskilling teams and addressing resistance to new technologies.

## Conclusion

Generative AI and traditional predictive models each offer unique advantages for forecasting in local businesses. While traditional methods provide simplicity and reliability, Generative AI introduces advanced capabilities for dynamic and detailed forecasting. The choice between these approaches depends on factors such as business size, industry, budget, and technological readiness. By understanding the nuances of both methods, local businesses can make informed decisions to enhance their forecasting practices and achieve sustained growth.

The future of generative AI in business forecasting lies in its ability to become more precise, adaptive, and accessible, reshaping decision-making across industries. Advances in model architectures, such as reinforcement learning and multimodal AI, will enable deeper integration of diverse data types, from numerical and textual to visual and geospatial information. Businesses will leverage real-time forecasting powered by generative AI to react instantly to market dynamics, supply chain disruptions, and consumer behavior shifts. Ethical and interpretable AI solutions will gain prominence, ensuring transparency and accountability while maintaining accuracy.

Moreover, the democratization of generative AI through user-friendly tools and platforms will allow small and medium-sized enterprises to harness its potential, leveling the competitive playing field. As AI continues to evolve, its role in predictive analytics will move beyond forecasting to include prescriptive insights, providing businesses with actionable recommendations to optimize operations and drive innovation.

Generative AI represents a transformative leap in business forecasting, addressing the limitations of traditional predictive models and unlocking new opportunities for accuracy and adaptability. While implementation challenges exist, the potential benefits far outweigh the risks, positioning local businesses for a competitive edge in dynamic markets.

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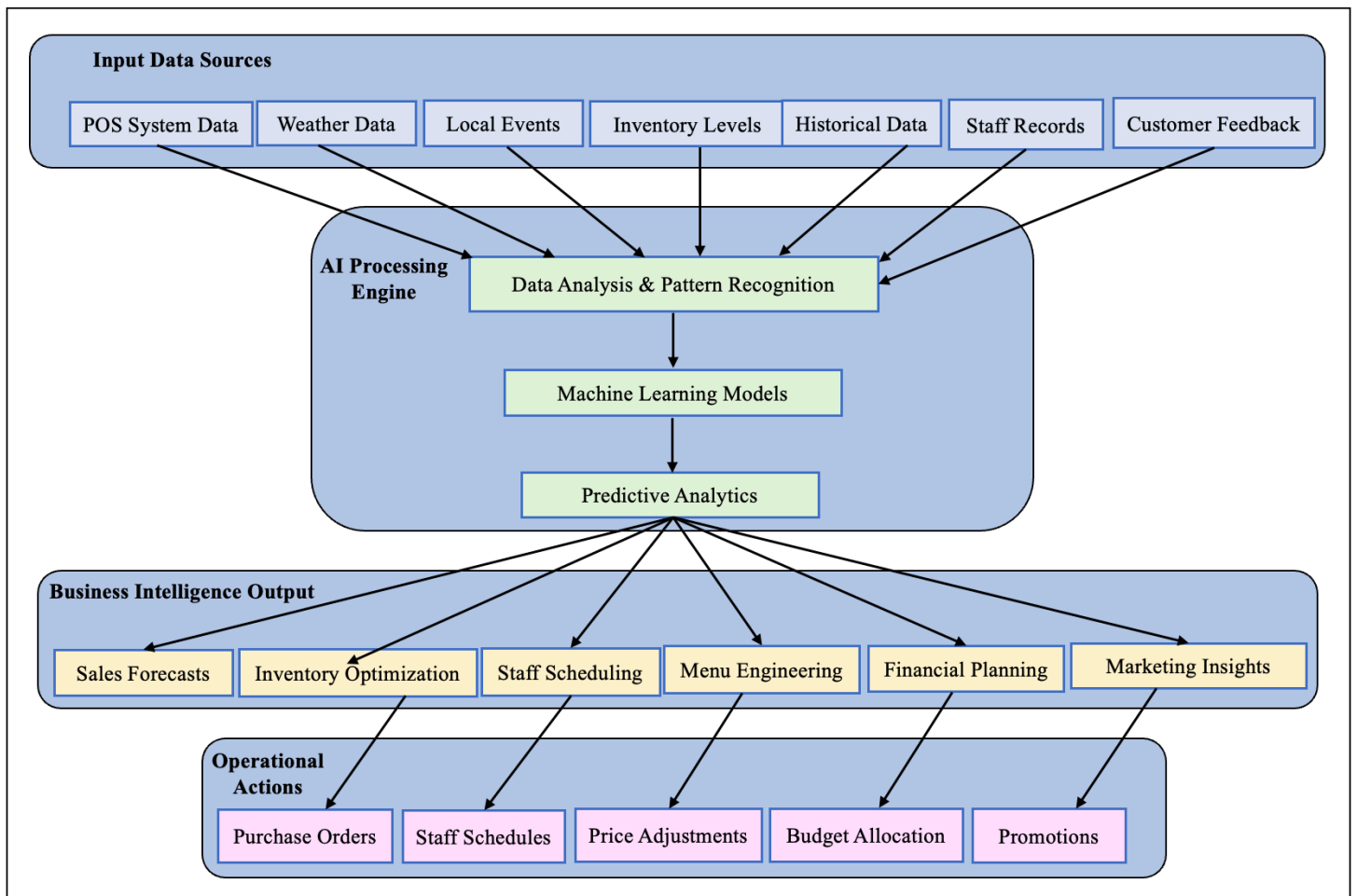
*Diagram 1: Flowchart for Applying Generative AI in Restaurant Forecasting*