

Predictive Food Demand Forecasting and Waste Reduction Using Machine Learning in Modern Catering Systems

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ABSTRACT

Purpose: Food waste represents one of the most pressing operational and sustainability challenges confronting the modern catering and hospitality industry. This study investigates how machine learning (ML) forecasting systems can substantially improve demand prediction accuracy, reduce food waste, and advance operational efficiency in commercial catering environments.

Design/methodology/approach: A multi-algorithm forecasting framework integrating Long Short-Term Memory (LSTM) networks, Random Forest, XGBoost, and an ensemble model was developed and evaluated using 24 months of operational data drawn from large-scale catering facilities. Internet of Things (IoT) sensor data capturing real-time inventory levels, environmental conditions, and consumption patterns were incorporated as supplementary input features. Model performance was assessed using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2).

Findings: The ensemble model achieved an MAPE of 5.4% and an R^2 of 0.94, outperforming all individual models and the ARIMA baseline by a substantial margin. Implementation of the AI-driven forecasting system was associated with a 36% reduction in weekly food waste, a 26.5% decrease in procurement costs, and a 66.3% reduction in monthly stockout incidents.

Research limitations/implications: Findings are based on a specific institutional context and may require adaptation for smaller or geographically diverse catering operations. Future research should explore real-time adaptive forecasting and explainable AI (XAI) frameworks.

Practical implications: The framework provides catering managers and hospitality executives with an evidence-based, data-driven decision-support tool capable of reducing operational costs, enhancing supply chain resilience, and advancing corporate sustainability objectives.

Originality/value: This study offers one of the first integrative comparisons of LSTM, Random Forest, XGBoost, and ensemble learning within a hospitality food service operations context, bridging the gap between computational forecasting literature and strategic management practice.

: Catering management; food demand forecasting; machine learning; food waste reduction; sustainable hospitality; predictive analytics; operational efficiency

PLAIN LANGUAGE SUMMARY

Every year, catering organisations across the world discard enormous quantities of food because demand is imperfectly anticipated. This inefficiency imposes direct financial costs on operators and contributes disproportionately to environmental harm through greenhouse gas emissions and resource depletion. This study demonstrates that artificial intelligence, specifically machine learning algorithms that learn from historical sales records, seasonal patterns, and real-time sensor data, can predict how much food will be required on any given day with high precision. By aligning procurement and preparation with accurate demand signals, catering managers can dramatically cut the volume of food that is never consumed, lower purchasing expenditure, and reduce last-minute supply shortfalls. The practical value of these findings extends beyond cost savings: organisations that adopt AI-powered forecasting are better positioned to meet corporate sustainability commitments, satisfy regulatory requirements on waste reduction, and enhance the dining experience through greater menu consistency. The tools and methods described in this study are applicable across institutional catering, hotel food and beverage operations, and large-scale restaurant chains.

1. INTRODUCTION

Food waste is a systemic problem of extraordinary scale. According to the Food and Agriculture Organization of the United Nations (FAO, 2023), approximately one-third of all food produced globally is lost or wasted, generating an estimated 8–10% of total greenhouse gas emissions. Within the hospitality and catering industry, food waste is disproportionately concentrated at the service stage, where misalignment between anticipated and actual customer demand results in over-preparation, spoilage, and disposal. The direct financial cost of this inefficiency is substantial: the hospitality sector in high-income economies spends an estimated 3–5% of total operating costs managing avoidable waste (Papargyropoulou et al., 2022).

Accurate food demand forecasting is widely recognised as the most operationally effective strategy for mitigating this problem. However, traditional forecasting approaches, including historical average methods and autoregressive integrated moving average (ARIMA) models, rely on assumptions of temporal stationarity and linear causality that are frequently violated in complex, event-driven catering environments (Wani et al., 2022). These methods struggle to capture the non-linear interactions among weather patterns, local events, day-of-week seasonality, menu composition, and promotional activity that collectively determine daily demand in modern food service settings.

Machine learning (ML) has emerged as a compelling alternative. Algorithms such as Long Short-Term Memory (LSTM) neural networks, Random Forest, and Extreme Gradient Boosting (XGBoost) are capable of identifying complex, non-linear patterns across high-dimensional data, making them well suited to the multifactorial demand environments characteristic of commercial catering operations (Cavaleri et al., 2021; Kim & Lee, 2023). Furthermore, the proliferation of Internet of Things (IoT) sensing infrastructure in smart kitchens and food storage environments has created new opportunities to enrich forecasting models with real-time data streams that were previously unavailable to operational decision-makers (Verdouw et al., 2021).

Despite these developments, the academic literature on ML-based food demand forecasting remains predominantly technical in orientation, with insufficient attention devoted to the managerial implications and strategic value of these systems for hospitality organisations (Tse & Poon, 2022). There is a particular gap in research that compares multiple ML architectures within an operational catering context and translates technical forecasting improvements into concrete managerial outcomes such as cost reduction, waste minimisation, and supply chain resilience.

This study addresses these gaps through four primary contributions. First, it develops and evaluates a comprehensive multi-algorithm forecasting framework encompassing LSTM, Random Forest, XGBoost, and an ensemble model, using 24 months of operational data from large-scale catering facilities. Second, it quantifies the managerial impact of improved forecasting accuracy on food waste, procurement costs, inventory performance, and customer satisfaction. Third, it integrates IoT-derived real-time features into the forecasting pipeline, demonstrating the value of smart kitchen

infrastructure for operational decision support. Fourth, it develops a framework for translating forecasting improvements into actionable strategies for catering managers, supply chain coordinators, and sustainability officers.

The remainder of this article is organised as follows. Section 2 reviews the relevant literature on AI in hospitality management, food waste reduction, and predictive analytics. Section 3 describes the data collection protocol, feature engineering process, and model training methodology. Section 4 presents the empirical findings. Section 5 interprets these findings in light of prior research and discusses theoretical contributions. Section 6 articulates the managerial implications of the study. Section 7 provides concluding remarks, acknowledges limitations, and outlines avenues for future research.

2. LITERATURE REVIEW

2.1 Food Waste in the Hospitality Industry: Scale, Causes, and Consequences

Food waste in hospitality operations constitutes a multidimensional management problem with economic, environmental, and reputational dimensions. Empirical studies consistently document waste rates of 20–40% of total food prepared in institutional catering settings, with over-preparation driven by inaccurate demand estimation identified as the primary contributory factor (Papargyropoulou et al., 2022; Pirani & Arafat, 2021). Beyond direct financial loss, wasted food generates substantial downstream costs associated with disposal, refrigeration energy, and greenhouse gas emissions from landfill decomposition, making waste reduction a central concern for sustainability-conscious hospitality organisations (Filimonau & Gherbin, 2017).

Existing waste management strategies in the hospitality sector have focused predominantly on behavioural interventions, portion size adjustment, and donation programmes (Chiu & Hsieh, 2023). While these approaches yield incremental improvements, they do not address the root cause of waste generation at the operational planning stage: the systematic mismatch between food production volumes and actual customer demand. Closing this gap requires predictive capability that traditional management practices have been unable to provide reliably.

2.2 Traditional Demand Forecasting: Capabilities and Limitations

Conventional demand forecasting in catering management has historically relied on moving averages, seasonal decomposition, and ARIMA-family models (Nikolopoulos et al., 2021). These methods offer interpretability and computational simplicity but are constrained by their inability to model non-linear relationships and their sensitivity to structural breaks caused by unexpected events such as public health crises, extreme weather, or sudden changes in customer composition (Wani et al., 2022). Empirical benchmarking studies have consistently found that ARIMA models produce MAPE values in the range of 12–18% for daily catering demand, a level of imprecision that translates to significant over-procurement and waste at scale (Cavaleri et al., 2021).

Exponential smoothing methods, while more adaptive than ARIMA, remain fundamentally univariate in their orientation and cannot incorporate the rich contextual information—event calendars, weather forecasts, menu change announcements, social media sentiment—that experienced catering managers routinely use informally when planning production volumes. This information asymmetry between human intuition and statistical models has motivated interest in ML-based forecasting architectures capable of processing multivariate, heterogeneous data at scale.

2.3 Machine Learning for Demand Forecasting: Evidence and Gaps

The application of ML to service industry demand forecasting has grown substantially since 2019. Empirical studies in adjacent domains, including hotel room demand (Hu et al., 2021), airline passenger volume (Zhang et al., 2022), and retail sales (Bandara et al., 2020), have demonstrated that ML models consistently outperform traditional statistical approaches, particularly in volatile demand environments where seasonality is complex and multiple external drivers are operative.

Within the food service sector specifically, Cavaleri et al. (2021) applied Random Forest and gradient boosting to restaurant meal demand forecasting and reported MAPE improvements of approximately 35% relative to ARIMA baselines. Kim and Lee (2023) demonstrated that LSTM networks were particularly effective for capturing weekly and monthly demand cycles in institutional catering settings, leveraging their recurrent architecture to retain information about longer-term consumption patterns. More recently, Tse and Poon (2022) proposed an ensemble framework combining gradient boosting with neural network components for food service demand prediction, reporting R^2 values exceeding 0.90 in a large-scale institutional setting.

However, several important gaps remain in the extant literature. First, most existing studies evaluate a single algorithm rather than comparing multiple approaches within a unified experimental framework, limiting the guidance available to practitioners selecting forecasting tools. Second, the integration of real-time IoT sensor data as a feature input has received limited empirical attention in the food service context, despite the rapid diffusion of smart kitchen infrastructure (Verdouw et al., 2021). Third, and most critically for the present study, the existing literature is predominantly technical in its framing, with limited discussion of how forecasting improvements translate into managerial outcomes such as cost reduction, waste minimisation, and supply chain optimisation (Song & Liu, 2023). This study directly addresses all three gaps.

2.4 IoT and Smart Kitchen Infrastructure

The emergence of affordable IoT sensing technology has substantially expanded the data available to food service operations managers. Smart inventory management systems equipped with weight sensors, RFID tracking, and temperature monitoring provide continuous, real-time data on stock levels, consumption rates, and storage conditions (Verdouw et al., 2021). Integrated with point-of-sale (POS) systems, these data streams enable far more granular demand signal extraction than weekly or daily sales summaries alone.

Several studies have examined the operational impact of smart kitchen adoption in isolation from forecasting applications. Duan et al. (2022) found that IoT-enabled inventory systems reduced spoilage by an average of 23% across a sample of mid-scale hotel food and beverage operations, primarily through real-time alert generation for near-expiry stock. Song and Liu (2023) demonstrated that incorporating IoT-derived real-time inventory data as ML model inputs improved demand forecast accuracy by 12–18% relative to models trained exclusively on historical sales data. These findings suggest a strong complementarity between smart kitchen infrastructure and ML forecasting systems that the present study seeks to validate and extend.

2.5 Sustainable Operations Management and the Role of Predictive Analytics

Sustainable operations management has emerged as a strategic priority for hospitality organisations responding to stakeholder pressure, regulatory requirements, and competitive differentiation imperatives (Chiu & Hsieh, 2023; Filimonau & Gherbin, 2017). Food waste reduction is increasingly embedded within corporate sustainability frameworks, with major international hotel groups committing to measurable waste reduction targets aligned with the United Nations Sustainable Development Goals (SDGs), particularly SDG 12 (Responsible Consumption and Production) and SDG 13 (Climate Action).

Predictive analytics has been identified as a key enabler of sustainable operations in multiple review studies (Song & Liu, 2023; Tse & Poon, 2022). By enabling proactive rather than reactive supply chain management, ML-based forecasting systems allow organisations to reduce over-procurement, minimise emergency disposal costs, and align production volumes with actual consumption capacity. This alignment between operational efficiency and environmental performance represents a significant strategic value proposition for hospitality organisations pursuing integrated sustainability strategies. A notable gap in the sustainable operations literature concerns the empirical quantification of sustainability improvements attributable to AI-driven forecasting adoption. Existing studies typically report either forecasting accuracy metrics or sustainability outcomes in isolation, without linking them through a coherent analytical framework. This study contributes to closing this gap by reporting both technical performance metrics and associated operational sustainability outcomes measured against a pre-implementation baseline.

3. METHODOLOGY

3.1 Research Design

This study adopts a quantitative, positivist research design grounded in secondary operational data analysis and machine learning model development. The methodological approach is consistent with design science research principles (Hevner et al., 2004), in which the research artefact—the multi-algorithm forecasting framework—is developed, evaluated, and assessed for practical utility within a real-world organisational context. The study employs a retrospective longitudinal design, using 24 months of historical operational data to train and validate forecasting models before assessing post-implementation operational performance changes.

3.2 Data Sources and Collection

The dataset was compiled from three large-scale institutional catering facilities operating within the hospitality sector, collectively serving a combined average of approximately 4,200 meals per day across breakfast, lunch, and dinner service periods. The facilities encompass hotel food and beverage operations, corporate catering services, and event-based catering, providing heterogeneous demand environments suitable for assessing model generalisation across catering sub-sectors.

Primary data sources included: (1) point-of-sale (POS) transaction records capturing daily meal counts by dish category, service period, and customer segment; (2) IoT-enabled inventory management system logs recording real-time stock levels, consumption rates, and temperature monitoring data at 15-minute intervals; (3) kitchen production records documenting preparation quantities and recorded waste volumes; (4) external contextual data encompassing local event calendars, weather records (temperature, precipitation, and humidity), and regional public holiday schedules. The combined dataset comprised 87,600 daily observations across the 24-month study period, with 70% of data allocated to model training, 15% to validation, and 15% to out-of-sample testing.

Data preprocessing involved multiple sequential steps. Missing values attributable to system downtime (£3.2% of observations) were imputed using linear interpolation for numerical variables and mode imputation for categorical variables. Outlier identification employed the interquartile range (IQR) method, with observations falling more than three IQRs from the median flagged for manual review. Temporal features were engineered to capture day-of-week, week-of-month, month, and seasonal effects. Categorical variables were encoded using one-hot encoding, and all continuous features were normalised to the [0,1] range using min-max scaling to prevent scale-dependent algorithmic bias.

3.3 Feature Engineering

Feature engineering constituted a critical step in model development, reflecting the multifactorial nature of catering demand. Thirty-two input features were constructed across five categories. Temporal features ($n = 8$) captured day-of-week, service period, week number, month, quarter, and binary indicators for weekends and public holidays. Historical consumption features ($n = 10$) incorporated rolling averages, standard deviations, and lag variables at 7-day, 14-day, and 28-day intervals, capturing short- and medium-term consumption trends. IoT-derived features ($n = 7$) included real-time inventory levels, consumption rate indices, and temperature anomaly indicators from smart kitchen sensors. Contextual features ($n = 4$) covered weather variables (maximum temperature, precipitation probability) and local event attendance estimates. Menu-level features ($n = 3$) captured dish category composition, price tier distribution, and promotional offer status on any given day.

Feature importance analysis was conducted using Random Forest permutation importance scores to identify and retain the most predictive variables, ensuring model parsimony without sacrificing predictive validity. The top fifteen features by importance score were retained in final model specifications, with the full thirty-two-feature model used as a robustness check.

3.4 Machine Learning Models

3.4.1 Long Short-Term Memory (LSTM) Networks

LSTM networks were selected as the primary deep learning architecture due to their demonstrated capacity to capture long-range temporal dependencies in sequential data, an attribute particularly well suited to the autocorrelated daily demand patterns characteristic of institutional catering (Kim & Lee, 2023). The LSTM architecture was configured with two stacked recurrent layers of 128 and 64 units respectively, followed by a dropout layer (rate = 0.2) to mitigate overfitting, and a fully connected output layer. The model was trained using the Adam optimiser with an initial learning rate of 0.001, and early stopping with a patience parameter of ten epochs was implemented to prevent over-training. A 30-day sliding window was used as the input sequence length, reflecting the temporal horizon most relevant for operational planning in the study facilities.

3.4.2 Random Forest

Random Forest was included as a robust ensemble method that has demonstrated consistent strong performance across service industry demand forecasting benchmarks (Cavaleri et al., 2021). Random Forest aggregates predictions from a large number of independently trained decision trees, each constructed on a bootstrapped sample of the training data and a random subset of input features. This design provides inherent resistance to overfitting and generates informative feature importance scores that can guide managerial interpretation of key demand drivers. The model was configured with 500 estimators, a maximum depth of 20 nodes, and the square root of the total number of features as the feature subset parameter at each split.

3.4.3 XGBoost

Extreme Gradient Boosting (XGBoost) was selected as a gradient boosting method known for its computational efficiency and strong performance on structured tabular data (Chen & Guestrin, 2016). Unlike Random Forest, which trains trees independently, XGBoost builds trees sequentially, with each tree correcting the prediction errors of its predecessor. Hyperparameter optimisation was conducted using five-fold cross-validation grid search across learning rate (0.01–0.3), maximum tree depth (4–10), and number of estimators (100–500), yielding an optimal configuration of learning rate = 0.05, depth = 7, and n_estimators = 300.

3.4.4 Ensemble Learning

An ensemble model combining the predictions of the LSTM, Random Forest, and XGBoost models was constructed using a stacking approach. A meta-learner—specifically a ridge regression model—was trained on the out-of-fold predictions of the three base models on the validation set, learning the optimal linear combination of base model outputs to minimise overall prediction error. This approach preserves the complementary strengths of each base model: the LSTM's capacity for temporal pattern recognition, the Random Forest's robustness and interpretability, and XGBoost's efficiency in capturing feature interactions.

3.5 Evaluation Metrics

Model performance was evaluated using four complementary metrics. Root Mean Squared Error (RMSE) penalises large prediction errors more heavily than smaller ones, making it sensitive to operationally costly under-procurement events. Mean Absolute Error (MAE) provides an interpretable average prediction error in original units. Mean Absolute Percentage Error (MAPE) enables scale-independent comparison across dish categories and service periods with differing demand volumes. The coefficient of determination (R^2) quantifies the proportion of demand variance explained by each model. All metrics were computed on the held-out test set to ensure unbiased performance estimation.

4. RESULTS

4.1 Model Performance Comparison

Table 1 presents the out-of-sample forecasting performance of all models evaluated in this study. The ensemble model achieved the highest performance across all four evaluation metrics, recording an RMSE of 15.7, an MAE of 11.9, an MAPE of 5.4%, and an R^2 of 0.94. These results represent a substantial improvement over the ARIMA baseline (MAPE = 12.6%, R^2 = 0.72), confirming that ML-based approaches offer materially superior demand forecasting capability in the study context.

Table 1. Out-of-Sample Forecasting Performance of Machine Learning Models and ARIMA Baseline

Model	RMSE	MAE	MAPE (%)	R^2
LSTM (Long Short-Term Memory)	18.3	13.7	6.2	0.91
Random Forest	22.1	16.4	7.8	0.87
XGBoost	20.5	15.1	7.1	0.89
Ensemble (LSTM + RF + XGB)	15.7	11.9	5.4	0.94
ARIMA (Baseline)	34.8	27.3	12.6	0.72

Note. RMSE = Root Mean Squared Error; MAE = Mean Absolute Error; MAPE = Mean Absolute Percentage Error; R^2 = Coefficient of Determination. All metrics are computed on the held-out test set (15% of total observations). Lower values indicate better performance for RMSE, MAE, and MAPE; higher values indicate better performance for R^2 .

Among individual models, the LSTM achieved the lowest MAPE (6.2%) and highest R^2 (0.91), reflecting its capacity to capture the weekly and seasonal demand cycles prevalent in institutional catering. Random Forest performed moderately (MAPE = 7.8%, R^2 = 0.87), while XGBoost occupied an intermediate position (MAPE = 7.1%, R^2 = 0.89). The superiority of the ensemble model over all individual models is consistent with theoretical expectations regarding variance reduction through model averaging (Tse & Poon, 2022) and aligns with empirical findings in adjacent forecasting domains (Hu et al., 2021; Zhang et al., 2022).

Feature importance analysis identified IoT-derived real-time inventory levels, 7-day lagged consumption, day-of-week, and local event attendance as the four most influential predictors across all models. Weather variables contributed meaningfully to LSTM performance but showed lower importance rankings in the tree-based models, a pattern consistent with the differential capacity of recurrent architectures to integrate time-varying contextual signals.

4.2 Operational Impact Assessment

To assess the real-world operational impact of the forecasting framework, the ensemble model was deployed in a pilot implementation across one of the three study facilities over a six-month period, following a 30-day parallel running phase to validate live performance. Operational metrics were compared against the same six-month period in the preceding year (pre-implementation baseline), with the resulting performance indicators reported in Table 2.

Table 2. Operational Performance Indicators: Pre- and Post-AI Forecasting Implementation

Performance Indicator	Baseline (Pre-AI)	Post-AI Implementation	Improvement (%)	Statistical Significance
Food Waste (kg/week)	142.6	91.3	36.0%	$p < 0.001$
Procurement Cost (USD/week)	8,420	6,190	26.5%	$p < 0.01$
Inventory Turnover Rate	2.1	3.4	+61.9%	$p < 0.05$
Stockout Incidents (per month)	9.2	3.1	66.3%	$p < 0.001$
Customer Satisfaction Score	3.8/5.0	4.5/5.0	+18.4%	$p < 0.05$

Note. Statistical significance was assessed using paired *t*-tests comparing weekly values across equivalent six-month periods. Baseline period: equivalent calendar months in the preceding year. Post-AI period: six months of live ensemble model deployment.

The most pronounced operational improvement was observed in the stockout incident rate, which declined by 66.3% from 9.2 to 3.1 incidents per month ($p < 0.001$). This reduction reflects the ensemble model's improved capacity to anticipate demand surges associated with local events and seasonal patterns, enabling proactive procurement adjustments that buffer against supply shortfalls. Food waste volumes declined by 36% from a baseline of 142.6 kg per week to 91.3 kg per week ($p < 0.001$), a reduction with both direct financial value and substantial sustainability significance.

Weekly procurement costs decreased by 26.5%, from USD 8,420 to USD 6,190, generating an annualised cost saving of approximately USD 117,000 for the single pilot facility. Inventory turnover improved by 61.9%, indicating that procurement quantities were more precisely aligned with actual consumption, reducing the average age of inventory and lowering spoilage risk. Customer satisfaction scores, as measured by post-meal survey instruments, improved from 3.8 to 4.5 on a five-point scale ($p < 0.05$), suggesting that the reduction in stockout incidents translated into improved menu availability and service consistency from the customer's perspective.

5. DISCUSSION

5.1 Theoretical Contributions

The findings of this study make several contributions to the intersection of management science and hospitality operations research. First, the consistent superiority of the ensemble model over individual ML algorithms and the ARIMA baseline corroborates theoretical arguments for predictive model diversity and variance reduction in complex demand environments (Tse & Poon, 2022). The degree of performance improvement over ARIMA—a reduction in MAPE from 12.6% to 5.4%—substantially exceeds the improvements reported in adjacent studies (Cavaleri et al., 2021; Kim & Lee, 2023), suggesting that the integration of IoT-derived features provides meaningful additional predictive value beyond what historical sales data alone can supply.

Second, the positive contribution of IoT sensor features to model performance validates the theoretical framework proposed by Verdouw et al. (2021) regarding the complementarity of smart infrastructure and analytical intelligence in agri-food supply chains. The present study extends this framework to the food service operations domain, demonstrating that real-time inventory and consumption data from smart kitchens constitutes a genuinely valuable source of demand signal rather than merely supplementary noise.

Third, the operational impact results provide empirical grounding for the proposition that forecasting accuracy improvements translate into measurable managerial outcomes with strategic significance. The 36% reduction in food waste

and 26.5% reduction in procurement costs represent outcomes that are directly relevant to corporate sustainability reporting, ESG performance assessment, and operational financial management in hospitality organisations—connecting technical ML performance to the strategic management frameworks through which hospitality executives evaluate investment decisions.

5.2 Comparison with Prior Research

The MAPE of 5.4% achieved by the ensemble model compares favourably with the best results reported in recent comparable studies. Cavaleri et al. (2021) reported MAPE values of 6.8–8.3% for gradient boosting and Random Forest models applied to restaurant demand forecasting. Kim and Lee (2023) achieved MAPE values of 6.1–7.4% using LSTM architectures in institutional catering contexts. The improvement beyond these benchmarks in the present study may be attributable to two factors: the integration of IoT-derived real-time features as supplementary inputs, and the adoption of a stacking ensemble approach that captures complementary information from architecturally diverse base models.

The operational waste reduction of 36% reported here is broadly consistent with, though somewhat below, the upper bound of reductions reported in IoT-exclusive (non-ML) interventions by Duan et al. (2022), who found waste reductions of 23–41% across different operational contexts. This comparison suggests that ML-based forecasting and IoT infrastructure deployment may exert partially overlapping effects on waste reduction, and that studies examining these interventions in isolation may overestimate the marginal contribution of either technology when deployed independently.

5.3 Limitations

Several limitations of the present study warrant acknowledgement. The empirical evaluation was conducted within a specific set of large-scale catering facilities in a single geographic and regulatory context, which may constrain the generalisability of the findings to smaller-scale operations, culturally distinct market contexts, or food service environments characterised by substantially different demand volatility profiles. The six-month pilot implementation period, while sufficient to demonstrate directional impact, may not capture the full performance trajectory of the forecasting system as it accumulates additional training data and undergoes operational fine-tuning.

Furthermore, the current framework does not incorporate natural language processing of customer feedback, social media sentiment, or unstructured external data sources that experienced catering managers recognise as valuable informal demand signals. The absence of explainability mechanisms represents a practical limitation for managerial adoption: while the ensemble model achieves high accuracy, its composite architecture makes individual prediction reasoning opaque to non-technical users. Future research incorporating explainable AI (XAI) approaches, such as SHapley Additive exPlanations (SHAP) values or Local Interpretable Model-Agnostic Explanations (LIME), would substantially enhance the practical accessibility of ML forecasting tools for catering management practitioners.

6. MANAGERIAL IMPLICATIONS

The findings of this study carry substantive implications for several categories of hospitality management practitioners, extending beyond the technical domain of algorithm selection to encompass strategic planning, operational management, and sustainability governance.

6.1 Implications for Catering Operations Managers

Catering managers and food and beverage directors stand to benefit most directly from ML forecasting adoption. The ability to produce daily demand forecasts at the dish-category level with MAPE values below 6% enables a fundamental shift from reactive, experience-based procurement decision-making to proactive, evidence-based operational planning. The 66.3% reduction in stockout incidents documented in this study indicates that ML forecasting substantially reduces the frequency of the operationally disruptive supply failures that currently absorb disproportionate management time and negatively affect

service quality. Practically, this capability allows managers to renegotiate supplier contracts on more favourable terms by committing to stable, predictable order patterns, and to schedule kitchen staff and preparation time more precisely, reducing overtime and idle time costs.

The feature importance results also carry direct operational guidance value. The high predictive weight of local event calendars and day-of-week variables suggests that catering managers should ensure systematic data collection on event schedules and invest in CRM systems that link customer segment composition to demand outcomes. These data enrichment investments will compound in value as the ML system accumulates additional training observations over time.

6.2 Implications for Hotel and Restaurant Supply Chain Management

For supply chain and procurement managers operating across multi-site hospitality portfolios, the findings suggest that ML forecasting offers a scalable mechanism for achieving centralised demand visibility and coordinated procurement optimisation. The 26.5% reduction in weekly procurement costs achieved in the pilot facility translates to substantial cumulative savings at enterprise scale: a hospitality group operating twenty comparable facilities could anticipate annualised procurement savings in the range of USD 2.3 million based on the metrics documented in this study. Beyond direct cost reduction, improved forecast accuracy enables procurement teams to reduce safety stock holdings, negotiate more favourable just-in-time delivery arrangements with perishable goods suppliers, and shift from reactive to collaborative supply chain relationships.

6.3 Implications for Sustainability Officers and ESG Reporting

The 36% reduction in food waste documented in this study represents a concrete, quantifiable sustainability improvement that is directly relevant to corporate ESG reporting frameworks and stakeholder accountability mechanisms. Food waste reduction contributes measurably to progress against SDG 12 (Responsible Consumption and Production) and generates carbon footprint reductions across the entire disposal value chain. For hospitality organisations that have committed to the UN Global Compact or sector-specific sustainability frameworks such as the Sustainable Hospitality Alliance roadmap, ML-driven forecasting adoption offers a credible and auditable mechanism for demonstrating progress against waste reduction targets. Sustainability officers should therefore collaborate with operations and IT teams to embed forecasting performance metrics within sustainability KPI dashboards and investor communication frameworks.

6.4 Implications for Hospitality Executive Leadership and Strategic Planning

At the strategic leadership level, the findings of this study support the business case for sustained investment in AI and data infrastructure within hospitality organisations. The estimated payback period for ML forecasting system implementation, based on documented procurement cost savings and waste reduction outcomes, falls within the 8–12-month range that typically satisfies hospitality capital investment thresholds. Beyond financial returns, AI-driven operational intelligence provides a competitive differentiation pathway in a sector where product quality and cost efficiency are simultaneously emphasised. Executive leaders should consider AI forecasting adoption as a component of broader digital transformation strategies, ensuring that organisational culture, staff training, and data governance frameworks are developed in parallel with technological capability.

7. CONCLUSION

This study has demonstrated that a multi-algorithm machine learning forecasting framework, integrating LSTM networks, Random Forest, XGBoost, and an ensemble model with IoT-derived real-time features, offers materially superior demand forecasting performance relative to traditional ARIMA approaches in large-scale catering management contexts. The ensemble model achieved a MAPE of 5.4% and an R^2 of 0.94 on out-of-sample test data, and its deployment in a six-

month pilot implementation was associated with a 36% reduction in food waste, a 26.5% decrease in procurement costs, a 66.3% reduction in stockout incidents, and an 18.4% improvement in customer satisfaction scores.

These outcomes are not merely technical achievements. They represent a meaningful advancement in the operational capability of catering organisations to manage food resources sustainably, efficiently, and responsively. The study contributes to the management literature by providing an empirically grounded, managerially framed account of how AI-driven forecasting systems can be designed, evaluated, and implemented to generate strategic value across multiple dimensions of hospitality operations performance.

Future research should explore the following directions. First, the application of explainable AI frameworks—including SHAP value analysis and counterfactual explanation methods—would enhance the managerial accessibility and trust-building capacity of ML forecasting tools, particularly for non-technical end users. Second, adaptive online learning approaches that continuously update model parameters as new operational data arrive would address the temporal drift limitations of static model training. Third, multi-site comparative studies spanning diverse geographic, cultural, and institutional catering contexts would enhance the generalisability of findings and identify context-specific moderating factors that influence AI forecasting adoption outcomes. Finally, research examining the organisational change management dimensions of AI system implementation in hospitality settings would complement the technical and operational findings of the present study by addressing the human and cultural factors that ultimately determine whether analytically superior systems are adopted and used effectively in practice.

DISCLOSURE STATEMENTS

Conflict of Interest: The author declares no conflict of interest.

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Data Availability Statement: The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Ethical Statement: This research does not involve human participants or animal subjects.

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