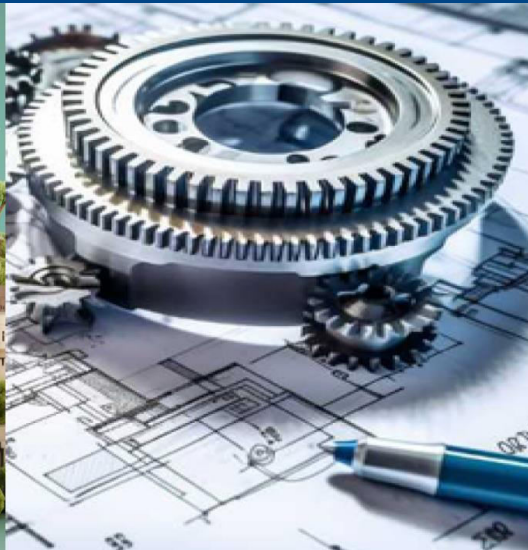
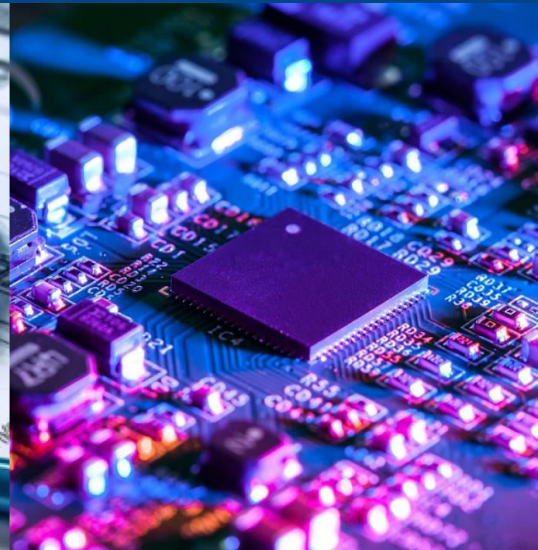
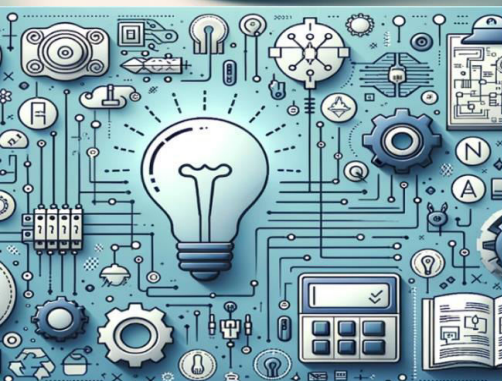




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Demand Forecasting Practices and Operational Efficiency: An Empirical Study of Café Businesses in Mysuru

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ABSTRACT: Demand in cafés varies hourly, weekly, seasonally and according to local events, and most raw materials are perishable. Mysuru had 338 cafés in April 2026, of which 91% were single-owner and planned purchasing, staffing and production without the analytical support available to chains. The literature suggests that accurate forecasting improves inventory control, reduces waste and supports resource planning, but previous work focuses on forecasting accuracy in retail, canteens, hotels and large restaurant groups. There is little understanding of how small, independent cafés forecast demand, or how those practices promote operational efficiency. This paper explores the demand forecasting practices of cafés in Mysuru and assesses their influence on operational efficiency in terms of inventory management, waste reduction, labour efficiency, cost control and overall performance. A quantitative, descriptive, cross-sectional design was followed. A 25-item questionnaire (14 items on forecasting practices; 11 on operational efficiency; five-point Likert scale) was administered in person to 128 café respondents, showing good internal consistency (Cronbach's $\alpha = .845$). Exploratory factor analysis (principal components, varimax rotation, SPSS) identified four dimensions of forecasting practice (Forecasting Integration, Demand Analysis, Demand Planning and Forecast Utilization; KMO = .726; 54.41% of variance) and three dimensions of operational efficiency (Operational Efficiency, Resource Management and Operational Performance; KMO = .713; 50.79% of variance). Two multiple regression models were significant overall, $F(7, 120) = 27.15$, $p < .001$, adjusted $R^2 = .59$ (overall efficiency) and $F(7, 120) = 25.11$, $p < .001$, adjusted $R^2 = .57$ (inventory alignment). Among the forecasting dimensions, only Forecasting Integration had a significant positive effect, on inventory alignment ($\beta = .228$, $p = .004$), which suggests that forecasts gain value by being embedded into purchasing, staffing and review routines rather than simply analysed. Since the efficiency dimensions were entered alongside the forecasting dimensions, the high R^2 values should be read with caution. The paper offers an empirically derived measurement structure, evidence-linked strategies and a phased roadmap for independent cafés. It recommends a multi-city probability sample, structural equation modelling and POS records to measure forecast error and wastage directly.

KEYWORDS: demand forecasting; operational efficiency; cafés; inventory management; waste reduction; exploratory factor analysis; multiple linear regression; Mysuru.

I. INTRODUCTION

1.1 Background

Demand forecasting is the estimation of what customers are likely to buy over a given future period. For any business that holds stock, schedules staff or prepares products in advance, the forecast is the starting point for most operating decisions: how much to buy, how much to prepare and how many people to roster. Poor forecasts show up quickly as stock-outs that disappoint customers, over-production that ends as waste, idle labour in quiet periods and overstretched staff in busy ones.

Food-service businesses face this problem in an acute form. Products are perishable, lead times are short, and demand changes with the hour, the weather, festivals and local events. Cafés, which mainly serve beverages, snacks, light meals and bakery products for dine-in or takeaway, are an interesting setting because most are small, owner-managed businesses that make forecasting decisions daily, often on experience rather than formal analysis. Mysuru illustrates this well (Table 1).



International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Table 1. Café sector in Mysuru (SmartScrapers, 2026).

Indicator	Value
Cafés in Mysuru (April 2026)	338 (2.70% higher than in 2023)
Single-owner cafés	307 (90.83%)
Cafés belonging to larger brands	31 (9.17%)
Average age of a café	4 years 2 months
Market trend	Shift from filter-coffee culture towards specialty coffee, artisanal beverages, experiential cafés and bakery concepts (Times of India, 2025)

The sector is therefore made up of many young, independent operators who compete on differentiated experiences. For such businesses, efficient day-to-day operation is closely tied to how well they anticipate demand. A café that over-prepares absorbs the cost of waste, one that under-prepares loses sales and goodwill, and one that mis-rosters staff pays for idle time or serves slowly.

1.2 The forecasting and operations system

Although the size of the café and the tools that they use might be different, the cycle of decision-making remains the same (Figure 1). The signals about the expected demand, such as previous sales, the day of the week and specific time of the day, seasons, holidays, and events, are processed into a forecast. The forecast is then used to establish purchases, the quantities of production, and the staff schedule. These decisions will then affect the services provided and the efficiency outcomes that the owner wants to reach: the stock that meets the demand, little to no waste, short wait time for the customers, and low costs. The last step of the cycle is comparing the forecast against the actual sales to close the loop. Since the decisions are made sequentially, the failure at one stage, such as producing the goods without using the forecast, creates multiple inefficiencies further down the process.

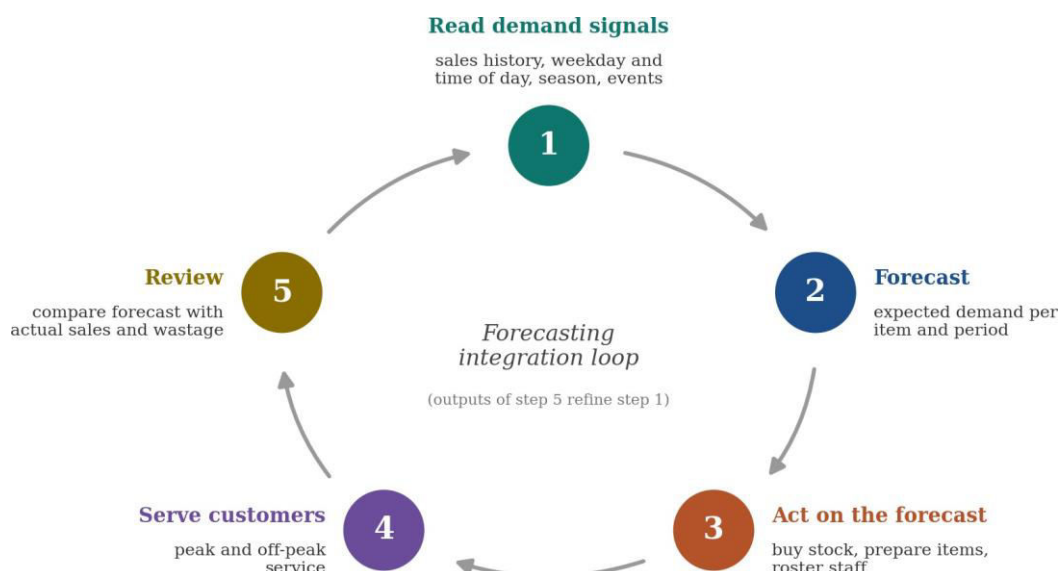


Figure 1: Generalised forecasting-to-operations flow in a café (author's schematic based on the literature and questionnaire design).



International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

1.3 Concepts

The café processes two particular concepts. Demand forecasting practices are activities that a café undertakes to predict and exploit demand, which involve using historical data, recognizing patterns, accounting for seasonality and events, binding demand to purchase and staff, and auditing the forecast against demand. Forecasting methods are either judgemental, time-series (moving average, exponential smoothing, ARIMA), causal (regression), or machine-learning-based (Random Forest, XGBoost, LSTM). Food-service research reports a shift towards evidence-based practices, where machine-learning-based models reduced food waste by 14–52% compared to baseline forecasting in catering (Rodrigues et al., 2024); artificial intelligence (AI)-based demand forecasts outperformed human counterparts in a food and beverage outlet (Groene and Zakharov, 2024); and exogenous variables (weather, holidays, and events) proved more informative than sales history (Kamola and Arabas, 2020; Rekiek, Jebari and Reklauoi, 2024).

Operational efficiency is the ratio of a process that transforms resources (inventory, labor, time, and money) into the service that a customer pays for with minimal expenses and delays. For a café, it takes the form of a combination of stock management without waste, staff scheduling aligned with demand, waiting time reduction, cost reduction within a given scope, and order accuracy in the timeframe specified. Forecasting is expected to affect all of the above in that it provides the decision-making basis for purchases, preparation, and labor (Chandran and Khan, 2024; Arguelles and Polkowski, 2023). Table 2 below specifies the areas of decision-making affecting efficiency that were considered in this study.

Table 2. Café decision areas linking forecasting to efficiency.

Decision area	What the forecast informs	Efficiency outcome examined
Purchasing	Quantity of ingredients and other inventory	Inventory alignment; fewer stock-outs
Preparation	Quantity prepared in advance	Less wastage from over-preparation
Staffing	Number of employees per operating period	Staff allocation; shorter waiting time
Day-to-day planning	Regular input to daily operations	Smooth service at peak demand; cost control
Review	Forecast compared with actual sales; learning from past forecasts	Better future forecasts; overall efficiency

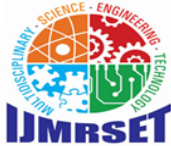
1.4 Motivation and problem

Four considerations motivate the study. Firstly, accurate forecasting enables better purchasing, production, and resource allocation, so its role in daily café operations needs to be understood (Chandran and Khan, 2024). Secondly, forecasting can improve operational and supply-chain performance, but the extent of improvement differs across business contexts (Arguelles and Polkowski, 2023), which calls for a test within cafés specifically. Thirdly, café demand fluctuates with time, day, season, and preferences (Kumar and Chansoria, 2024). Fourthly, data-driven forecasting is growing in the literature, but small and independent cafés receive little attention compared to retail, manufacturing, and larger hospitality firms.

The research problem, then, is: to what extent do the demand forecasting practices adopted by café businesses in Mysuru influence their operational efficiency, and how can that efficiency be improved? The paper sets out the literature and gaps (Section 2), objectives and scope (Section 3), methodology (Section 4), factor-analysis results (Section 5), regression results (Section 6), strategies (Section 7), a discussion (Section 8), and concludes with limitations (Section 9).

II. LITERATURE REVIEW AND RESEARCH GAP

We reviewed 37 studies on demand forecasting, inventory management and operational efficiency in food service and hospitality. Three are Indian studies on the human and skills side of hospitality operations; the remainder are international or general supply-chain and forecasting studies.



International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

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Indian studies

2.1 Indian work in the review focuses on people rather than forecasts. Theirs is training and development that improve productivity, service quality, and morale and reduce wastage (Amirtharaj, Raja Cross and Vembar, 2011); skill-gaps and turnover, which increase costs and decrease efficiency (Laghane and Deshmukh, 2012); and the mismatch between the analytical and technological capabilities required and those possessed (Kumar and Chansoria, 2024). None explores how cafés can forecast demand. Evidence base for Mysuru is limited to the description of the market for cafes (SmartScrapers, 2026; Times of India, 2025).

2.2 International and conceptual studies

Forecasting Accuracy: In food contexts, machine-learning often outperforms traditional benchmarks. Random Forest and LSTM decreased waste by 14-52% and unfulfilled demand by 3-16% in canteen data (Rodrigues et al., 2024), boosted ensemble trees achieved $R = 0.96$ in a university refectory (Aci and Yergök, 2023), LSTM variants excelled on a huge food-demand data set (Panda and Mohanty, 2023), and AI forecasts beat direct comparisons with managers by 6.5-33.3% in RMSE and MAE in a food and beverage outlet (Groene and Zakharov, 2024). A review of 29 restaurant forecasting studies finds that most focus on model accuracy and rarely combine several internal and external factors (Choi, Zhang and Nadzri, 2022).

External Factors: Event data lifted hospitality forecasts up to 4% on event days (Kamola and Arabas, 2020), and weather and events improved hotel-booking forecasts (Rekiek, Jebari and Reklaoui, 2024). **Inventory and Cost Outcomes:** ARIMA-based material planning decreased restaurant inventory costs (Puspita, Primadani and Susanti, 2020), forecast mean error had a larger impact on profits than variance error (Zhou, Shen and Yu, 2023), modelling demand dependence increased contribution margin in food service (Rojas, 2019), and forecasting and management accounting systems increased inventory efficiency in cafés and restaurants (Puspitawati, Lhutfi and Qudratov, 2024). **Organisation and Adoption:** More developed, integrated forecasting processes were associated with higher levels of manager satisfaction in restaurant corporations (Green, 2001). SMEs tend to rely on spreadsheets and subjective estimates and struggle with poor data (Haataja, 2016). Forecasting effectiveness is influenced by the degree of market adaptability, implementation cost and ease of integration (Chandran and Khan, 2024) and Big Data improved supply-chain performance through forecasting in UAE hospitality (Arguelles and Polkowski, 2023). AI affords SMEs opportunities in forecasting and inventory but faces cost, data and skills obstacles (Lu et al., 2022; Verma, 2024).

2.3 Research gaps

Five gaps emerge. This paper addresses the first directly and the second and fourth in part, through the café setting, an inventory-alignment outcome and the demand-planning items; the other two are left to future work because they need different data (Table 3).

Table 3. Research gaps and how this study treats them.

Gap	Nature	Treatment here
1	Limited café-specific research; most studies cover hotels, restaurants, canteens, retail and manufacturing (Rodrigues et al., 2024; Groene and Zakharov, 2024)	Addressed by primary survey of 128 Mysuru café respondents
2	Forecasting and inventory studied separately (Seyedan, 2023; Zhou, Shen and Yu, 2023)	Partly addressed: inventory alignment is tested as an outcome (Model 2)
3	Perishability and waste overlooked (Puspita, Primadani and Susanti, 2020; Leuveano et al., 2023)	Not addressed directly; wastage is one survey item; listed as future work
4	Real-world demand factors (seasonality, holidays, weather, promotions) inconsistently used (Choi, Zhang and Nadzri, 2022)	Partly addressed: seasonality and event items form the Demand Planning dimension
5	Practical AI adoption in small businesses underexplored (Lu et al., 2022; Verma, 2024)	Not addressed; listed as future work



International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

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In addition, no study located in the review examines the demand forecasting practices of Mysuru cafés, or the Indian café segment more broadly, using primary survey data. The study therefore fills a contextual, empirical and practical gap.

III. OBJECTIVES AND SCOPE

Aim. To examine the demand forecasting practices adopted by café businesses in Mysuru and assess their influence on operational efficiency, particularly inventory management, waste reduction, labour efficiency, cost savings and overall operational performance.

Four objectives follow, each paired with a research question. Objectives 1 and 2 are exploratory (factor identification), Objective 3 is confirmatory-style hypothesis testing, and Objective 4 draws the results together.

Table 4. Objectives, research questions and evidence.

Objective	Research question	Method / evidence
O1. Identify the factors of demand forecasting practices	RQ1. What are the underlying dimensions of forecasting practices adopted by Mysuru cafés?	EFA of 14 items; n = 128
O2. Identify the factors of operational efficiency	RQ2. What are the underlying dimensions of operational efficiency in cafés?	EFA of 11 items; n = 128
O3. Examine the relationship between forecasting practices and operational efficiency	RQ3. To what extent do forecasting practices influence operational efficiency?	Multiple regression on factor scores
O4. Recommend strategies to improve operational efficiency	RQ4. What strategies can cafés adopt to improve efficiency through better forecasting?	Synthesis of O1–O3, literature and fieldwork insights

Scope. The study is bounded by place (Mysuru, Karnataka; sampling frame of 338 cafés in April 2026), business (food and beverage establishments serving beverages, snacks, light meals and bakery items, both independent and branded), concepts (forecasting practices and operational efficiency as defined in Section 1.3), method (cross-sectional survey analysed by factor analysis and regression) and time (primary data collected in 2026). The study does not build or test a forecasting algorithm; it examines the practices cafés follow and their association with perceived efficiency.

IV. METHODOLOGY

4.1 Research design

The study follows a quantitative, descriptive and cross-sectional design with a deductive approach: constructs and relationships were drawn from the literature, operationalised in a structured questionnaire and tested with primary data collected at one point in time (Figure 2). The unit of analysis is the café, and respondents are people responsible for or closely involved in operating decisions (owners, managers, supervisors and operations or kitchen staff). Data were collected by in-person administration at café premises under convenience sampling.



International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

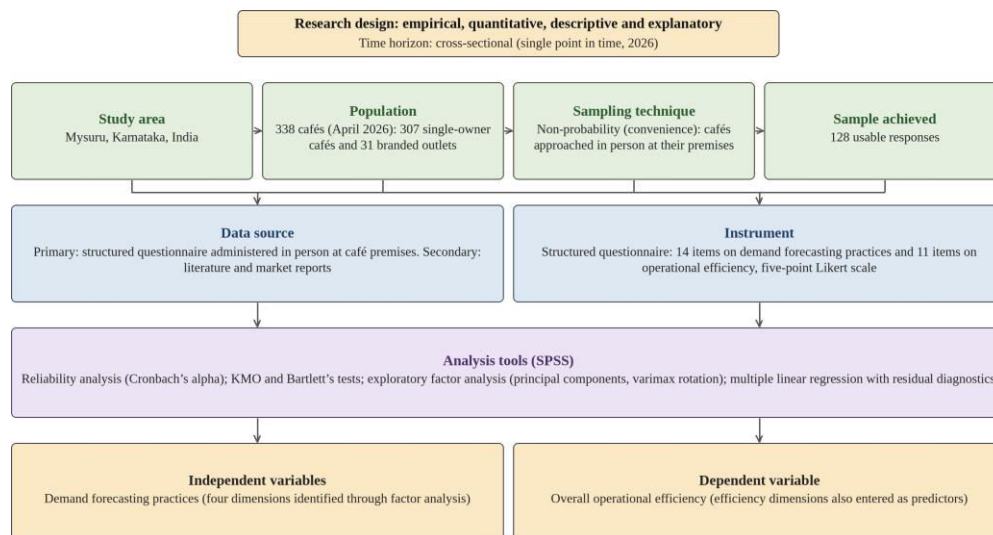


Figure 2. Research design of the study.

4.2 Conceptual framework

The framework developed from the literature (Figure 3) treats demand forecasting variables (forecast accuracy, forecasting model or technique, demand planning effectiveness and forecast utilization) and operational efficiency variables (labour efficiency, cost savings, waste reduction and inventory management) as independent variables, with overall operational efficiency as the dependent variable. It was specified before analysis. Factor analysis then showed how the items actually group, and the regression models use those empirical dimensions as predictors.

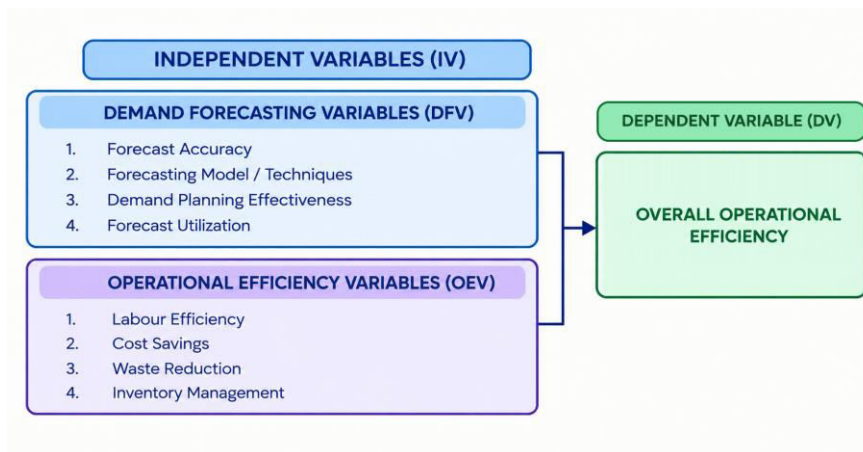


Figure 3. Conceptual framework of the study.

4.3 Hypothesis

Because the impact of forecasting practices, the effectiveness of those practices and the relationship between forecasting and efficiency address the same underlying question, a single hypothesis was tested at $\alpha = .05$, with the overall model assessed by the F test and each predictor by its t statistic and standardised coefficient (β).

H1: demand forecasting practices, and the effectiveness with which they are applied, have a significant relationship with and impact on the overall operational efficiency of cafés in Mysuru.



International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

4.4 Sampling

The population is 338 cafés. Finite-population benchmarks at 95% confidence, 5% margin of error and $p = 0.5$ are about 184 (Yamane, 1967) and 181 (Cochran, 1977, finite-corrected). The achieved sample was 128 usable responses (37.9% of the population), smaller than the benchmark, as is common with time-constrained small-business owners, and gives a margin of error of about $\pm 6.8\%$ at 95% confidence. Its adequacy for the techniques used was checked directly (Table 5).

Table 5. Adequacy of the achieved sample ($n = 128$).

Technique	Guideline	Position in this study
Exploratory factor analysis	At least 5–10 respondents per item (Hair et al., 2019)	$128/14 = 9.1$ and $128/11 = 11.6$ per item
Multiple regression	$n \geq 50 + 8m$ (Green, 1991)	$50 + 8 \times 7 = 106$; achieved 128
Sampling precision	5–7% generally acceptable in exploratory business research	$\pm 6.8\%$ at 95% confidence

Table 6 profiles the respondents. About 41% were owners or managers (24.2% and 26.6%), almost half had one to three years of experience in café operations, and most cafés had 1–20 employees and served 50–200 customers a day. Some 60.2% reported that demand fluctuates sometimes and 14.0% often or very often.

Table 6. Profile of respondents and cafés ($n = 128$).

Variable	Category (frequency, %)
Designation	Café owner 31 (24.2); manager 34 (26.6); supervisor 20 (15.6); operations staff 24 (18.8); kitchen/production staff 19 (14.8)
Experience in café operations	Under 1 year 18 (14.1); 1–3 years 61 (47.7); 4–6 years 38 (29.7); 7–10 years 11 (8.6)
Number of employees	1–5: 43 (33.6); 6–10: 43 (33.6); 11–20: 36 (28.1); 21–30: 6 (4.7)
Customers served daily	Under 50: 24 (18.8); 50–100: 41 (32.0); 101–200: 43 (33.6); 201–300: 17 (13.3); over 300: 3 (2.3)
Demand fluctuations	Never 4 (3.1); rarely 29 (22.7); sometimes 77 (60.2); often 15 (11.7); very often 3 (2.3)

4.5 Questionnaire

The questionnaire was prepared from the food-service forecasting literature (for example Green, 2001; Chandran and Khan, 2024; Puspitawati, Lhutfi and Qudratov, 2024; Rodrigues et al., 2024). Section A records respondent and café profile. Section B has 14 items on forecasting practices (use of historical data, analysis of patterns, weekday, seasonal and event effects, use of forecasts for purchasing and staffing, review against actual demand). Section C has 11 items on operational efficiency (inventory levels, stock-outs, wastage, resource use, staff allocation, service continuity, waiting time, cost control, order fulfilment and overall efficiency). Items are positive statements about the respondent's own café, rated from 1 (strongly disagree) to 5 (strongly agree) (Likert, 1932). Example items: "Our café uses demand forecasts to determine the quantity of ingredients and other inventory that needs to be purchased" (Q7) and "Our café minimizes food and beverage wastage caused by preparing more than the actual customer demand" (Q17).



International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

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4.6 Verification and validation

Reliability. Cronbach's alpha for the 25 items is .845, above the .70 threshold (Nunnally, 1978; Cronbach, 1951). Alpha-if-item-deleted ranged from .830 to .851, and no deletion would raise alpha by more than .006, so all items were kept. Content validity rests on items drawn from constructs repeatedly used in the literature, although no formal expert panel was used. Construct validity was examined by factor analysis: KMO was .726 and .713 with significant Bartlett tests ($p < .001$) (Kaiser, 1974; Bartlett, 1954; Field, 2018); components were retained by the eigenvalue-above-one rule (Kaiser, 1960) and scree inspection (Cattell, 1966); all retained loadings exceeded .40 (lowest .426) with no cross-loadings above the display threshold. Regression checks comprised F tests, RZ and adjusted RZ, and residual plots: mean residual about zero, SD of standardised residuals .972, roughly bell-shaped histograms and P-P plots close to the diagonal with some mid-range departure, more marked for Model 1. Variance inflation factors were not part of the outputs reviewed.

V. FACTOR ANALYSIS RESULTS (OBJECTIVES 1 AND 2)

Fieldwork covered cafés across Mysuru, including Jayalakshimpuram, Vijay Nagar 2nd Stage, Vani Vilas Mohalla and Kalidasa Road (Figure 4).

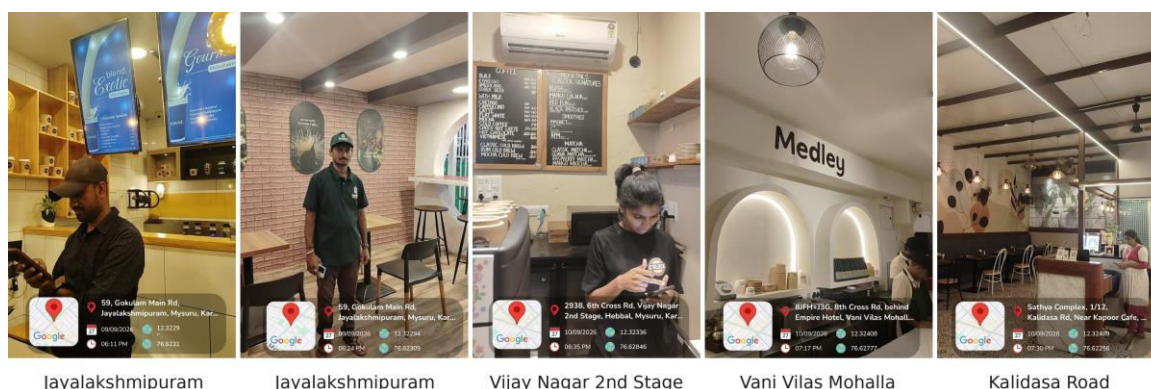


Figure 4. Geo-tagged fieldwork photographs from café visits in Mysuru (September 2026).

5.1 Factors of demand forecasting practices (Objective 1)

The 14 forecasting items were analysed by principal component extraction with varimax rotation. Sampling adequacy was good (KMO = .726) and Bartlett's test was significant ($\chi^2 = 342.27$, $df = 91$, $p < .001$). The scree plot (Figure 5) falls steeply and then flattens. Four components had eigenvalues above one and explained 54.41% of the variance (Table 7); after rotation the variance is spread more evenly (17.10, 13.91, 13.26 and 10.14%).

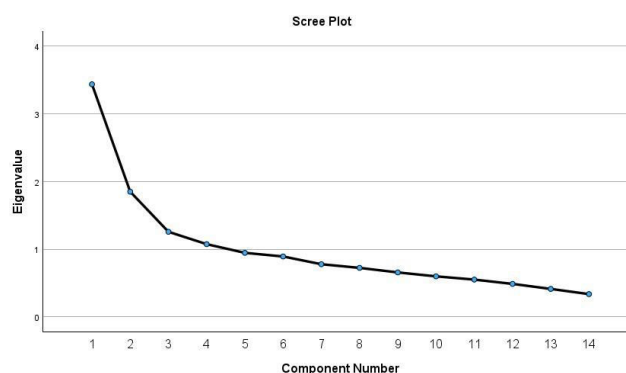
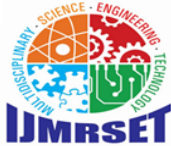


Figure 5. Scree plot: demand forecasting practices.



International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Table 7. Total variance explained (retained components).

Construct	Comp.	Eigenvalue	% variance	Cumulative %	Rotated %	Rotated cum. %
Forecasting practices	1	3.436	24.546	24.546	17.097	17.097
	2	1.849	13.210	37.756	13.907	31.004
	3	1.257	8.979	46.735	13.260	44.264
	4	1.074	7.673	54.408	10.144	54.408
Operational efficiency	1	3.008	27.344	27.344	20.747	20.747
	2	1.414	12.850	40.194	17.759	38.507
	3	1.165	10.595	50.789	12.282	50.789

Table 8. Rotated component matrix: demand forecasting practices.

Dimension (mean loading; SD)	Item	Loading
Forecasting Integration (.686; .141)	Q10 Plans staff numbers from expected demand	.775
	Q7 Uses forecasts to set ingredient and inventory purchases	.760
	Q11 Has a defined process to prepare and review forecasts	.733
	Q14 Uses past forecast results to improve future forecasts	.477
Demand Analysis (.685; .072)	Q13 Uses available sales and operational data	.768
	Q2 Analyses past sales patterns for changes in demand	.644
	Q1 Uses historical sales data to forecast demand	.642
Demand Planning (.579; .126)	Q4 Considers seasonal variations	.730
	Q5 Considers festivals, holidays and special events	.687
	Q12 Uses forecasts as a regular input to daily operations	.542
	Q6 Monitors changes in customer preferences and trends	.511
Forecast Utilization (.674; .147)	Q8 Regularly compares forecast with actual demand	.426
	Q3 Considers weekday, weekend and time-of-day differences	.778
	Q9 Adjusts forecasts when demand or conditions change	.570

Forecasting Integration has the highest mean loading (.686) and is the most clearly defined dimension. Demand Analysis has the lowest SD (.072), so its items contribute most evenly. Demand Planning has the lowest mean loading (.579), with two items (Q8 .426, Q6 .511) only moderately strong, and Forecast Utilization has the highest SD (.147). Café forecasting is therefore not a single activity: cafés differ in how far they analyse data, plan for demand drivers, integrate forecasts into buying and rostering, and keep adjusting them. The emphasis on historical sales is consistent with the literature, in which past sales are the basic input to every method (Kolkova, 2020; Puspita, Primadani and Susanti, 2020). The seasonality and event items in Demand Planning match evidence that external factors improve accuracy (Kamola and Arabas, 2020; Groene and Zakharov, 2024), and the weaker definition of that dimension suggests planning for external drivers is the least consistently practised element (Choi, Zhang and Nadzri, 2022). The label for the two-item Forecast Utilization dimension is an interpretive judgement.

5.2 Factors of operational efficiency (Objective 2)

The 11 efficiency items were analysed in the same way ($KMO = .713$; Bartlett's $\chi^2 = 235.64$, $df = 55$, $p < .001$). Three components had eigenvalues above one and explained 50.79% of the variance (Table 7). The fourth had an eigenvalue of .980, marginally below the Kaiser criterion, and the scree plot (Figure 6) supports a three-component solution.



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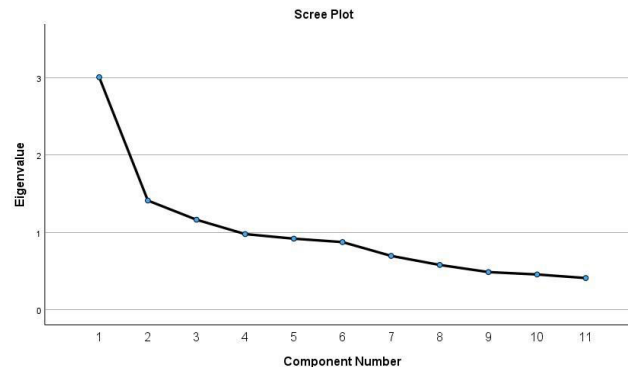


Figure 6. Scree plot: operational efficiency.

Table 9. Rotated component matrix: operational efficiency.

Dimension (mean loading; SD)	Item	Loading
Operational Efficiency (.633; .083)	Q21 Minimizes waiting time at high demand	.732
	Q15 Keeps inventory appropriate to expected demand	.696
	Q23 Controls operating costs while keeping service	.665
	Q19 Allocates staff according to demand variation	.661
	Q22 Smooth operations when demand changes	.603
	Q17 Minimizes wastage from over-preparation	.597
	Q16 Minimizes stock-outs of frequently demanded items	.479
Resource Management (.667; .071)	Q18 Makes efficient use of available resources	.717
	Q20 Smooth service during high demand	.616
Operational Performance (.675; .125)	Q25 Overall operates efficiently day to day	.763
	Q24 Fulfils orders within required service time	.586

Inventory, stock-out, wastage, staffing and cost items fall together in one broad dimension, suggesting that café managers experience them as aspects of the same daily control problem. Service speed and peak-period resource use separate into their own dimensions, so efficiency in cafés also has a customer-facing, time-sensitive side beyond stock and cost. The dimensions mirror the outcomes in the literature: inventory efficiency, waste reduction, resource utilisation and cost performance (Puspitawati, Lhutfi and Qudratov, 2024; Rodrigues et al., 2024; Zhou, Shen and Yu, 2023).

VI. REGRESSION RESULTS (OBJECTIVE 3)

6.1 Model specification and overall fit

Factor scores for the four forecasting and three efficiency dimensions were saved and entered together (method: Enter) in two models, each with seven predictors and 128 observations ($df = 7, 120$). Model 1 takes the overall-efficiency statement (Q25, “Overall, our café operates efficiently...”) as the dependent variable. Model 2 takes inventory alignment (Q15) as the dependent variable, a specific outcome that forecasting should influence directly. Both models were significant (Table 10).



International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Table 10. Regression model summary.

Statistic	Model 1 (overall efficiency)	Model 2 (inventory alignment)
R	.783	.771
RZ	.613	.594
Adjusted RZ	.590	.571
Std. error of estimate	.395	.472
F (7, 120)	27.147	25.109
Sig. (F)	< .001	< .001

6.2 Individual predictors

Table 11. Regression coefficients, Model 1 (dependent variable: overall efficiency).

Predictor	B	SE	β	t	p
(Constant)	4.070	.035		116.589	< .001
Forecasting Integration	.000	.047	.000	-.004	.997
Demand Analysis	.068	.041	.111	1.659	.100
Demand Planning	-.007	.040	-.011	-.176	.861
Forecast Utilization	.027	.041	.044	.652	.516
Operational Efficiency	.041	.048	.067	.853	.395
Resource Management	.035	.048	.057	.726	.469
Operational Performance	.483	.037	.783	13.233	< .001

Table 12. Regression coefficients, Model 2 (dependent variable: inventory alignment).

Predictor	B	SE	β	t	p
(Constant)	3.719	.042		89.148	< .001
Forecasting Integration	.164	.056	.228	2.917	.004
Demand Analysis	.068	.049	.095	1.386	.168
Demand Planning	-.008	.048	-.012	-.173	.863
Forecast Utilization	.011	.049	.015	.222	.824
Operational Efficiency	.021	.058	.030	.368	.713
Resource Management	.442	.058	.613	7.668	< .001
Operational Performance	.153	.044	.213	3.513	< .001



International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

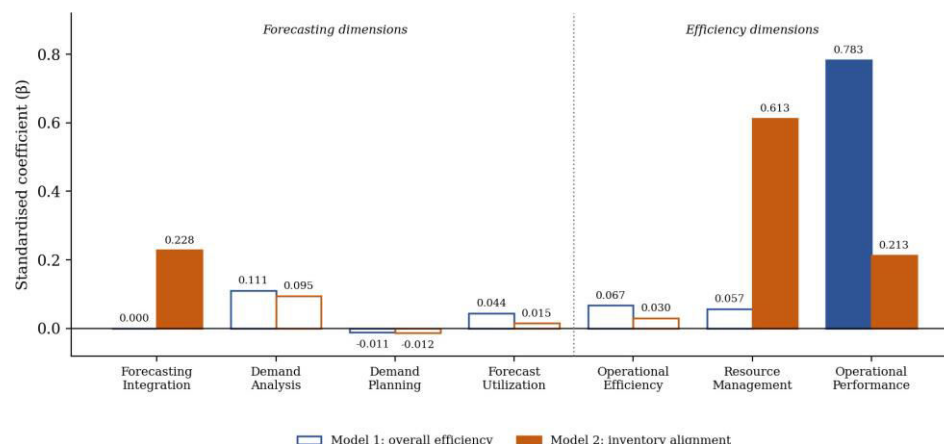


Figure 7. Standardised regression coefficients (β) by predictor and model (filled bars: $p < .05$).

In Model 1, only Operational Performance is significant ($\beta = .783$, $p < .001$); none of the four forecasting dimensions is (p from .100 to .997). In Model 2, Resource Management ($\beta = .613$), Forecasting Integration ($\beta = .228$, $p = .004$) and Operational Performance ($\beta = .213$) are significant and positive, while Demand Analysis, Demand Planning, Forecast Utilization and Operational Efficiency are not.

6.3 Reading the hypothesis

Table 13. Hypothesis testing summary.

Hypothesis	Evidence	Decision
H1: forecasting practices have a significant relationship with and impact on overall operational efficiency	Both models significant ($F = 27.147$ and 25.109 ; $p < .001$). At dimension level, only Forecasting Integration is significant (Model 2, $\beta = .228$, $p = .004$); no forecasting dimension is significant in Model 1; Forecast Utilization is not significant in either model.	Partially supported: at model level, and at dimension level only for Forecasting Integration

Two cautions govern interpretation. First, the efficiency dimensions are entered as predictors alongside the forecasting dimensions, and each dependent variable is itself an item loading on one of those dimensions. The RZ values therefore reflect shared content among efficiency items and should not be read as the share of efficiency explained by forecasting alone. Second, the sample is non-probabilistic and moderate in size, so results are indicative for Mysuru cafés rather than generalisable. The result for Forecasting Integration, the one forecasting effect that survives, is the more informative finding.

VII. STRATEGIES AND IMPLEMENTATION ROADMAP (OBJECTIVE 4)

Strategies were derived by triangulating the empirical findings (in particular the significance of Forecasting Integration and the low definition of Demand Planning), the literature on food-service forecasting and inventory, and practitioner insights gathered during fieldwork. Table 14 links each to its evidence.



International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Table 14. Recommended strategies to improve operational efficiency.

No.	Strategy	What cafés should do	Evidence base
1	Maintain accurate sales records	Record daily sales by item, day and time slot and review them regularly	Demand Analysis dimension; Haataja (2016)
2	Make better use of POS systems	Use POS data to find sales patterns and popular items rather than relying on memory	Q1, Q2, Q13; Puspitawati et al. (2024)
3	Combine data with experience	Use managerial experience to adjust data-based estimates, not replace them	Chandran and Khan (2024); Groene and Zakharov (2024)
4	Consider external factors	Keep a calendar of festivals, holidays, local events and weather effects and adjust expected demand	Demand Planning lowest loading; Kamola and Arabas (2020); Rekiek et al. (2024)
5	Review forecasts regularly	Compare forecast with actual sales weekly and revise the next forecast	Q8, Q14; Green (2001); Zhou et al. (2023)
6	Link forecasting with inventory and staffing	Set purchase quantities, stock levels and rosters from the forecast	Forecasting Integration $\beta = .228$
7	Adopt practical tools gradually	Start with spreadsheets; move to POS analytics or software as data, skills and budget allow	Lu et al. (2022); Chandran and Khan (2024)

Table 15. Indicative implementation roadmap for an independent café (proposal; not field-tested).

Phase	Actions	Indicators to track
1 (0–3 months): Foundation	Record item-wise daily sales; extract POS reports; compute average demand by weekday and time of day	Share of days with complete sales records
2 (3–6 months): Integration	Set purchases and rosters from the forecast; weekly forecast-versus-actual review; keep an events and festival calendar	Stock-out incidents; wastage as % of purchases; labour hours versus footfall
3 (6–12 months): Improvement	Introduce simple forecasting templates or software; add weather and event effects; train staff to use forecasts	Forecast error (e.g. MAPE); customer waiting time; operating cost ratio

VIII. DISCUSSION

Taken together, the results describe forecasting in small cafés as a set of related practices whose value depends on how they are used. Forecasting Integration is the only forecasting dimension with a significant effect, and it relates to the outcome that depends most directly on forecasts: having inventory that matches expected demand. Its items ask whether forecasts actually set ingredient quantities and staffing, whether a defined process exists, and whether past forecasts improve later ones. This agrees with evidence that more developed, integrated forecasting is associated with better outcomes (Green, 2001), that forecasting embedded in management accounting and information systems improves inventory efficiency (Puspitawati, Lhutfi and Qudratov, 2024), and that ease of integration is a significant success factor (Chandran and Khan, 2024). It also fits the observation that SMEs rely on subjective estimates and poor data (Haataja, 2016): analysing data matters little unless it informs decisions.

Demand Analysis, Demand Planning and Forecast Utilization showed no independent effect. Plausible explanations are that these practices are widespread but informal and so vary little across cafés, that they act mainly through integration, and that the efficiency dimensions in the same model absorb overlapping variance. These explanations were not tested and are offered as hypotheses for future work.

The practical message is encouraging for a sector in which about nine of ten cafés are independent and the average café



International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

is just over four years old: the practices that matter most (keeping sales records, linking forecasts to buying and rostering, and reviewing forecasts against actual demand) require discipline rather than expensive technology.

7.1 Contributions

- **Contextual:** to our knowledge, the first empirical evidence on forecasting practices and operational efficiency in the café sector of Mysuru.
- **Measurement:** a 25-item instrument with good reliability ($\alpha = .845$) and an empirical structure of four forecasting and three efficiency dimensions that others can reuse and validate.
- **Theoretical:** evidence that, in small food-service businesses, integrating forecasts into purchasing, staffing and review routines, rather than analysis alone, is the practice most associated with efficiency, complementing studies focused on model accuracy.
- **Practical:** evidence-linked strategies and a phased roadmap implementable with modest resources.

VIII. CONCLUSIONS, LIMITATIONS AND FUTURE WORK

8.1 Conclusions

- **Forecasting practices.** Four dimensions were identified (Forecasting Integration, Demand Analysis, Demand Planning, Forecast Utilization), explaining 54.41% of variance ($KMO = .726$).
- **Operational efficiency.** Three dimensions were identified (Operational Efficiency, Resource Management, Operational Performance), explaining 50.79% of variance ($KMO = .713$).
- **Relationship.** Both regression models are significant ($RZ = .613$ and $.594$; $p < .001$); Forecasting Integration is the only forecasting dimension with a significant positive effect ($\beta = .228$, $p = .004$, inventory alignment). H1 is partially supported.
- **Strategies.** Seven strategies and a three-phase roadmap focus on records, POS use, external factors, review and linking forecasts to inventory and staffing.

8.2 Limitations

Table 16. Limitations and how follow-up work can address them.

Limitation	Consequence	Remedy in follow-up work
n = 128, convenience sampling; below benchmark of about 180	Margin of error $\pm 6.8\%$; limited generalisability	Probability sample across cities
Self-reported, perceptual efficiency measures	Social-desirability and common-method bias	Combine with POS and purchase records: MAPE, wastage %, stock-out frequency
Efficiency dimensions entered as predictors; single-item dependent variables; VIF not reviewed	RZ inflated; causal reading limited	Composite efficiency index; collinearity checks; SEM (e.g. PLS-SEM)
Principal components with moderate variance explained; two-item dimensions	Interpretive labels	Confirmatory factor analysis
Cross-sectional, one city	No causal inference; findings may not hold for chains or other cities	Longitudinal and multi-city designs; moderators such as café size, age and POS use

Future work. Priorities are confirmatory modelling, objective performance data, the role of AI and machine-learning tools in small cafés (including cost, data and skills barriers; Lu et al., 2022; Groene and Zakharov, 2024), the effect of weather, festivals and tourism seasons on demand in a heritage and tourism city, and longitudinal follow-up of cafés that adopt formal forecasting.



International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

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