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Predictive Analytics for Demand Forecasting in the FMCG Sector: A Study of Consumer Purchase Patterns in Bengaluru

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ABSTRACT

In the present study, the authors investigate and assess the importance of predictive analytics in predicting the demand of Fast-Moving Consumer Goods (FMCG) with the analysis of consumer buying behavior using the urban consumers in Bengaluru. The primary data collected by the researcher were obtained by using a structured questionnaire from 110 respondents aged between 18 to 45 years, the monthly quantity of FMCG purchase served as the dependent variable while 5 consumer side demand drivers namely seasonality, promotional offers, price sensitivity, income effect, and product availability were the independent variables. Data analysis was conducted by using descriptive statistics, factor analysis, correlation analysis and multiple regression in Microsoft Excel (with XLSTAT add-on) and it was presented using Power BI dashboards with an ANOVA analysis. Five variables were identified as determinants of the demand: internal locus of control, entrepreneurial motivation, goal orientation, perceived behavioral control, and satisfaction with current working status. Factor analysis showed that these five variables load on a single component (Cronbach's Alpha = 0.797) and the correlation analysis revealed no indications of multicollinearity among the predictors. The overall regression model was statistically significant at $R^2 = 0.163$, Adjusted $R^2 = 0.123$, $F = 4.051$ ($p = 0.002$), where seasonality was the only variable with a statistically significant separate effect on purchase quantity ($p = 0.034$). The researchers found that the purchase amount was not significantly affected by promotional offers, price sensitivity, or the income effect at the 0.05 level, or product availability at the 0.01 level. The study results suggest that festive and seasonal cycles are the most significant on the consumer side for FMCG demand and that a FMCG purchase behaviour regression-based model derived from consumer survey data can meaningfully predict consumer purchase behaviour, providing a cost-effective, consumer-centric alternative to the traditional technique of transaction-based forecasting for FMCG companies.

Keywords: Predictive analytics, demand forecasting, FMCG sector, consumer purchase patterns, multiple regression, seasonality, Bengaluru

1. INTRODUCTION

1.1 Background

Fast-Moving Consumer Goods (FMCG) are the packaged products, such as beverages, food, and personal care and home cleaning products that the Indian consumers buy on a regular and daily basis, making it one of the most competitive and biggest sectors in India. Since the products are sold so often, the manufacturers and distributors rely largely on reliability in the estimation of demand to plan production and stock and marketing budgets.

However, India's consumer markets are very volatile, and demand forecast systems relying on past sales data and trend are finding themselves unable to match the rapidly-changing demands of consumers. In such a setting, there is no single demand driver out there that reliable decision making can be based on—in this situation, an approach which is able to simulate multiple synergistically related factors on the consumer side is needed. This helps to identify a clear need for a more systematic and data-driven approach for demand estimation.

This study aims to discuss problem of FMCG demand forecasting with regard to a urban consumer's perspective in context of Bengaluru. Contrary to many previous studies that forecast using the secondary data and information of the supply chain, this research directly collects first-hand consumer data aged between 18 to 45 years, and constructs multiple regression models for consumers' purchase behaviour. At the surface, the central research question for this study was: The factors affecting consumer purchase from an urban audience in Bengaluru in terms of frequency and quantity of buying of FMCG products – are there factors such as seasonality, promotional offers and price sensitivity that are significant determinants? They make use of a structured questionnaire, statistical analysis in MS Excel, and visualisation in Power BI, to simply answer this question.

1.2 Industry Profile: The Indian FMCG Sector

FMCG products have high turnover rate, low price, and reliable repeat-buying. Generally, in India, the industry is segmented into three categories: food and beverage, personal care products, and household and fabric care products. Other companies in the industry who are active participants in the Indian market are Hindustan Unilever Limited (HUL), ITC Limited, Nestlé India, Dabur India, Britannia Industries, Godrej Consumer Products and others.

The FMCG industry in India has seen an annual CAGR of 17.31% and was worth USD 210+ billion in 2023, expected to reach USD 884 billion by 2032 (IMARC Group, 2023) on account of increased income levels, urbanisation, rise of modern retail and rise in e-commerce and quick-commerce platforms.

The sector is still fragmented in terms of distribution. Traditional kirana stores remain predominant in rural and semi-urban India and modern trade format is gaining momentum in urban areas. Ecommerce is expected to be the fastest growing channel with sales representing approximately 7–10% of FMCG sales in 2024, and is projected to represent 15-18% of total sales by 2030.

The sales for FMCG products in Indian directly depend upon seasonality, promotion and price fluctuations. Around large festivals like Diwali or Navratri, people turn to food and personal care products even more than in their normal course, and even small price movements (10–15%) can lead to brand switching and/or to a lesser amount of the product purchased. The sector offers, therefore, an unusually high body of behavioural data and the very richness of that data and the variation from product type, consumer segment and location makes this a more challenging industry than some that are more stable for demand forecasting.

As a result, global FMCG manufacturers including Hindustan Unilever and Nestlé have started investing significantly in artificial intelligence technology to accurately predict demand, prevent out-of-stocks and optimize them budget. This study seeks to address those points as there was very little research published which has used customer insight and not transactions as the basis for FMCG demand forecasting in India with the underlying algorithms being proprietary.

1.3 Research Gap

The present study is motivated by three gaps found in the current literature. First, there is almost no cross referencing between the literature on demand forecasting and the literature in FMCG consumer-behavior in India. Forecasting studies like those of Punia and Shankar (2022), Fildes et al. (2022), Ceran et al. (2024), and Tarallo et al. (2019) develop predictive models based on past transaction data, scanner data or inventories data, but they do not gather original data regarding a consumer's purchase drivers. On the other hand, Indian studies on consumer behaviour like Sulekha and Mor (2013), Rajesh (2026) and Rao and Reddy (2025) were very good at gathering consumer data but did not use any of it to formulate a predictive model of demand. There is no existing study that has primary consumer survey data, regression based predictive model of the Indian FMCG sector.

Secondly, the urban consumer is almost completely ignored in the process of forecasting his/her demand in Bengaluru. Of the studies that were reviewed for this research, only one study investigated the consumers of FMCG products in Bengaluru, which was based on a descriptive approach and was not predictive. Most of the forecasting studies have used supermarket data from the west or east but the only India level study uses financial data of the companies not consumer data such as Sen & Chaudhuri (2017) which used the financial data of the companies. The population of Bengaluru is neither like the rural customers of Haryana and Rayalaseema of previous Indian studies nor is its interactive behavior of demand likely to be captured by existing demand models.

Third, while seasonality has been frequently pointed out as a significant factor in the demand of FMCG products, there is no study to statistically model festive season demand in urban India with primary consumer data. Bartwal et al. (2024), Fildes et al. (2022) and Hewage et al. (2026) report that seasonality is one of the most important and regular factors in FMCG demand; however, they determine it from transaction data, rather than from the perception and reaction of consumers to seasonality itself. Demand surges that come during festival days in India, such as Diwali, Navratri, Onam, Eid, or regional harvest festivals are overlapping culturally unique surges as there is demand data that cannot be captured by the transaction data alone. This study fills that void directly as it is based on consumers' response to what festivities they would want to purchase and includes it as a predictor in regression demand model in the city of Bengaluru.

1.4 Research Objectives

Objective 1: It aims to understand the effect of the drivers of the consumer side demand on consumers' buying of FMCG products in Bengaluru.

Objective 2: To understand the buying behaviour of FMCG products by consumers of Bengaluru.

Objective 3: To predict the FMCG demand with information from consumer surveys using multiple regression analysis.

Objectives 4: To discuss the degree of goodness of fit and test the statistical significance for the regression model using R2, Adjusted R2 and F Value to find out to what extent the consumption pattern variables explain the expenditure behaviour in FMCG.

1.5 Hypothesis

H_{01}: Festive and seasonal factors have no significant effect on the purchase quantity of FMCG products among consumers in Bengaluru.

H_{11}: Festive and seasonal factors have a significant effect on the purchase quantity of FMCG products among consumers in Bengaluru.

H_{02}: Promotional offers have no significant effect on the purchase frequency of FMCG products among

consumers in Bengaluru.
H_{12}: Promotional offers have a significant effect on the purchase frequency of FMCG products among consumers in Bengaluru.
H_{03}: Price changes have no significant effect on brand-switching behaviour and purchase quantity among FMCG consumers in Bengaluru.
H_{13}: Price changes have a significant effect on brand-switching behaviour and purchase quantity among FMCG consumers in Bengaluru.
H_{04}: A regression-based predictive model built from consumer purchase-pattern variables does not significantly predict FMCG demand.
H_{14}: A regression-based predictive model built from consumer purchase-pattern variables significantly predicts FMCG demand.

2. Literature Review

2.1 Theoretical Framework

Predictive analytics involves the use of historical data to identify patterns and make informed projections about future outcomes; in a business context, it is used to forecast demand, plan resources, and support decisions before problems arise. Demand forecasting, the specific application examined in this study, is the process of estimating the quantity of goods that customers will purchase in the future. Forecasting errors are costly in either direction: excess supply results in unsold inventory, while insufficient supply results in stockouts during periods of peak demand.
Three broad approaches to demand forecasting are recognised in the literature. The first relies on expert opinion and market surveys. The second applies time-series techniques such as moving averages and ARIMA models to historical sales data. The third, causal or regression-based forecasting, is more complex than the first two but is also more informative, because it identifies the underlying causes of demand – such as price, promotion, and seasonality – rather than simply extrapolating past trends. This study adopts the third approach, using multiple regression analysis, because it is statistically robust, relatively easy to interpret, and explains not only how much demand is likely to change but also why.
Consumer purchase behaviour – shopping frequency, expenditure levels, and the factors that drive changes in the quantity purchased over time – is understood in this study through two complementary theoretical lenses. The Demand Factor Model from economics identifies price, product substitutability, consumer income, and seasonal expectations as key determinants of quantity purchased. The Marketing Mix framework (the 4 Ps) emphasises price and promotion as firm-controllable levers that influence FMCG demand. Together, these frameworks justify the choice of seasonality, promotions, price sensitivity, income, and availability as the independent variables examined in this research.
Demand forecasting is particularly difficult in the Indian FMCG sector because of the distinctive buying behaviour of Indian consumers. Demand surges around festivals such as Diwali, Navratri, Eid, Ugadi, and regional harvest seasons are difficult to capture through simple historical averages. High price sensitivity, the rapid growth of quick-commerce platforms such as Blinkit and Zepto, and the continued coexistence of kirana stores alongside organised retail add further complexity. Bengaluru, with its large population of students, IT professionals, and migrant workers, represents one of India's most dynamic and fast-changing FMCG markets, making it a particularly relevant setting for this study.

2.2 Empirical Studies

2.2.1 Predictive Analytics and Demand Forecasting Models

Punia and Shankar (2022) developed and tested a deep learning-based predictive analytics system for demand forecasting and found that models incorporating multiple demand-influencing variables, rather than relying solely on historical sales, produced significantly more accurate forecasts. This finding establishes the core logic underpinning the present study: that a multi-variable predictive model outperforms a simple historical average. Punia et al. (2020) reached a similar conclusion after testing LSTM networks and random forests across multiple retail channels, finding that models combining several demand drivers with historical sales data consistently outperformed models based on sales history alone – a finding that supports this study's use of multiple regression with five independent variables.

Fildes et al. (2022), reviewing decades of retail forecasting research, identified promotional events, seasonal cycles, and price elasticity as the three most consistently significant demand drivers across retail categories – the same three variable clusters measured in this study. They also observed a persistent gap between sophisticated academic forecasting models and the simpler tools practitioners actually use, which partly motivates this study's use of an interpretable regression model. Aichner and Santa (2023) similarly found that while machine learning models demonstrate strong predictive power in FMCG forecasting, they are often too complex for practitioners to interpret and trust, whereas regression models produce transparent coefficients that clearly show how a unit change in a driver affects demand.

Sen and Chaudhuri (2017) conducted one of the few published forecasting studies specific to the Indian FMCG sector, testing six time-series approaches and finding that decomposition-based methods, which separate trend, seasonal, and cyclical components, produce reliable forecasts for Indian FMCG data; their finding that seasonality is a structurally important component of Indian FMCG demand directly supports Hypothesis 1 of this study. Tarallo et al. (2019) found that even basic machine learning and statistical models outperform intuition-based forecasting among FMCG practitioners, supporting the case for structured analytical models generally. Ceran et al. (2024) found that models trained on consumer-side variables – purchase frequency, basket size, and promotional response – generated stronger demand predictions than supply-side inventory models alone, directly supporting this study's use of consumer survey data rather than company transaction records. Haque et al. (2023) similarly found that multivariate regression models incorporating several demand-driver variables consistently outperformed univariate historical-trend models, reinforcing the methodological choice made in this study.

2.2.2 Promotional Influence on FMCG Demand

Abolghasemi et al. (2020) discovered that typical forecasting models without promotional variables lead to underestimation of demand during promotional time periods, resulting in stockouts, and overestimation immediately after the promotional period, as consumers who stocked up during promotions start to run out of them. Adding the promotional variables to the regression model significantly reduced forecasting error by 23 to 41 percent. This finding directly informed the Hypothesis 2 of this study which test whether the promotional offers have a significant effect on purchase frequency of FMCG products among the consumers living in Bengaluru. Ali et al. (2009) found that promotional periods generate a spike in demand, from 60 to 300 percent above baseline and concluded that any demand model without a promotional variable is structurally incomplete, adding to the justification for the inclusion of a promotional influence variable in this study.

Hewage et al. (2026) identified the entire promotional demand cycle: a pre-promotion anticipation dip, in-promotion spike, and post-promotion drop, and showed that the post-promotion drop is not a trivial event as it is just as damaging to retailers as the in-promotion spike, thus proving that the promotional response is a measurable and predictable pattern that can be captured by survey data. In a small trading company in Thailand, a developing market context similar to India, Chaowai and Chutima (2024) found that the use of promotional campaigns raised demand by 60% to 161% and that a regression model that includes promotional variables reduced the phenomenon of over- and under-ordering by 34%.

2.2.3 Seasonality as a Demand Driver

Bartwal et al. (2024) developed a combined SARIMA-regression model for FMCG products that have high seasonal demand and reported that when regression-based seasonal adjustment was added to the SARIMA model, the forecasting error (MAPE) was reduced by an average of 18 percent. Most important for this research, they observed that consumer-reported seasonality was very similar to actual seasonal sales data, giving them confidence that the measure of seasonality from the consumer survey was a valid proxy for the consumer's purchase behavior in the season – as used in this research with questions about purchase behavior in the festive season.

2.2.4 Indian Consumer Purchase Behaviour

Rajesh (2026) presented an empirical study on the Factors affecting FMCG Buyer Behaviour in Bengaluru District which concluded that among the various factors affecting the purchase decision, the four factors who account for the higher percentage are price, product quality, promotional offers and availability of brand in the city. The variable selection used in the present study is validated by the other study, which is the only one conducted in the same geography, since it uses a descriptive (non-predictive) design, which is part of the research gap the present study addresses. Sulekha & Mor 2013 surveyed 200 FMCG consumers in rural Haryana; their research was followed up with regression and factor analysis to arrive at three factors which strongly predicted the purchase frequency of consumers namely proportion of household income, price sensitivity and product availability in the market; this study set in rural Haryana provided a methodological precedent for Indian FMCG research as it combined consumer survey data and regression with factor analysis. The findings of Rao and Reddy (2025) who investigated the FMCG household product in the region of Rayalaseema showed that the packaging and the rate of availability both had significant impact on the quantity of items purchased, indicating the influential role of both the price and availability variables in this study.

2.2.5 Price Sensitivity and Its Effect on FMCG Purchase Decisions

The findings of Mamuya (2024) are directly relevant to the study with respect to hypothesis 3, which confirms that price sensitivity is statistically significant as it impacts on consumer brand switching, whereby price feeling restrained would cause a consumer to change to a cheaper alternative brand as compared to quantity reduction. Gupta et al. (2025) identified the interest in value-for-money pricing and the negative effect on volume but positive effect on brand aspiration found to be significant, thus accounting for the correlation between price sensitivity and increased purchase frequency as well as brand loyalty. To support Pandit et al.'s (2024) claims to being validated on the broader methodological approach, they showed that predictive analytics could be used on demographic data about consumer behaviour, not just for supply-chain optimisation, but for actionable information about the patterns of consumer desire from the buyer's side.

2.3 Summary of Literature

The literature reviewed supports the consistency across the literature that the best performing demand forecasting models include more than just sales data alone and that the three most consistently significant

FMCG demand drivers globally are seasonality, promotion, and price-sensitivity. In the meanwhile, the forecasting literature mostly engages transaction, scanner or firm level data while the Indian consumer-behaviour oriented literature depends on a descriptive approach, where no predictive model is created. The study has no existing study that integrates primary consumer survey with regression based predictive modelling of FMCG demand setting in an Indian event more specifically in Bengaluru. This study is poised to fill that void.

3. RESEARCH METHODOLOGY

3.1 Research Design

This research is descriptive and analytical with a combination of methods. The descriptive component analyses the purchasing patterns (frequency, motivations for buying and product categories) purchased and the analytical portion uses multiple regression analysis to establish the factors that most clearly explain the purchasing frequency and to create a demand forecasting model.

3.2 Data Sources

A structured questionnaire comprising of seven sections: Demographic profile, FMCG purchase behaviour, seasonal purchase behaviour, influence of promotions, price change and product switching, product availability, and impact of income on demand were used for collecting primary data. For the behavioural items, a five-point Likert scale was used; for the demographic items categorical or ordinal scales were used. Peer-reviewed journal articles and research papers published between 2017 and 2026 were used to obtain the secondary data.

3.3 Sample and Sampling Design

For this study, a total of 110 responses were collected, and this constituted the sample. This sample size reasonably meets common guidelines of 10 cases per independent variable for multiple regression analysis, and is appropriate for the number of independent variables included in this model. Students and general population between 18-45 years of age who buys FMCG products and lives in Bengaluru participated in the study. It started by designing the sampling technique, which was an amalgamation of convenience sampling, as the respondents like students and working professional in Bengaluru were easily available, and purposive sampling, so that only active FMCG consumers were sampled for the study.

3.4 Scope of the Study

The geographical scope of the study is limited to Bengaluru, Karnataka, with all primary data collected from residents of the city. The study focuses on the highest-selling FMCG categories among urban consumers – food and beverages, personal care items, and household cleaning products – and examines a demand-side forecasting model only, without extending into supply-chain or production-side operations.

3.5 Variables of the Study

Purchase quantity (Y) of FMCG by the consumer is the dependent variable and it is measured in their monthly expenditure upon purchasing FMCG products. To help predict this, five independent variables (X_1–X_5) were used, as summarised in Table 1.

No.	Independent Variable	How It Is Measured
X_1	Seasonal / Festive Demand Effect	Composite Likert-scale score
X_2	Promotional Offer Influence	Composite Likert-scale score

No.	Independent Variable	How It Is Measured
X_3	Price Sensitivity / Brand Switching	Composite Likert-scale score
X_4	Income Level Effect	Monthly income bracket and income-spend response
X_5	Product Availability Effect	Composite Likert-scale score

3.6 Statistical Tools and Analysis

Descriptive statistics (mean and standard deviation) was computed for all variables using Microsoft Excel and the XLSTAT add-on. Factor analysis was used to determine the factors underlying the data and their reliability, as they were the variables that predicted monthly levels of FMCG purchases. A correlation matrix was computed to determine relationships between the independent variables and monthly FMCG spending, and a multiple regression analysis to determine which of the demand-driver variables significantly predicted monthly FMCG purchase quantity was conducted. A multiple regression analysis was also conducted, followed by an ANOVA to determine overall significance of the regression model. Consumer purchase trends, comparison of expenditure on different demand drivers, expenditure per category and distribution by demographics were all visualised using Power BI. The tests of hypotheses were carried out at the 95% confidence level ($p<0.05$).

4. ANALYSIS AND INTERPRETATION

4.1 Descriptive Analysis

Variable	Mean	Mode	Standard Deviation
Seasonality	3.93	4	0.89
Promotions	3.70	4	0.97
Price Sensitivity	3.40	4	1.12
Income Effect	3.24	4	1.28
Availability	3.55	4	1.09

Table 1: Descriptive Statistics of Demand Driver Variables

The highest mean score is for the Festive and seasonal factors (3.93) that mean that they are most affected by FMCG purchasing behaviour among respondents, followed by Promotions (3.70) and Availability (3.55). The Price sensitivity and the Income effect had a comparatively low influence, at 3.40 and 3.24, respectively. The high mode value for all variables reflects a general agreement with the underlying statements, and the relatively low standard deviation for each variable (0.89 to 1.28) represents a moderate amount of variation in answers for the individual variables.

Rank	Variable	Mean
1	Seasonality	3.93
2	Promotions	3.70

Rank	Variable	Mean
3	Availability	3.55
4	Price Sensitivity	3.40
5	Income Effect	3.24

Table 2: Demand Driver Ranking

Seasonality was the strongest determinant of FMCG buying habits, followed by Promotions and Availability, and Price Sensitivity and Income Effect were the least. This means that during the festive period and when there is promotional activity, responses are more affected than by price or income considerations for FMCG purchases. When asked the one most important factor influencing the monthly purchases of FMCG products, the leading responses were 'household necessity' (43 respondents), 'available discount' (25 respondents) and 'festival season' (19 respondents) indicating that, in this sample, the need to purchase FMCG products is the most important factor with festival season and discount the secondary ones.

4.2 Factor Analysis

The five composite demand-driver variables were submitted to Factor analysis based on XLSTAT and the method used for extraction was Principal Factor Analysis.

	F1	F2	F3
Eigenvalue	2.200	0.445	0.066
Variability (%)	43.99	8.90	1.31
Cumulative (%)	43.99	52.89	54.21

Table 3: Eigenvalues

Variable	F1	F2	Initial Communality	Final Communality
Average Seasonality	0.300	-0.459	0.131	0.301
Average Promotion	0.579	-0.311	0.291	0.432
Average Price Sensitivity	0.677	-0.055	0.390	0.461
Average Availability	0.794	0.073	0.536	0.636
Average Income Effect	0.828	0.359	0.523	0.815

Table 4: Factor Loadings and Communalities

Factor	Cronbach’s Alpha
F1 (XLSTAT validated)	0.797

Factor	Cronbach's Alpha
F1 (Overall Construct)	0.754

Table 5: Cronbach's Alpha

One dominant factor (F1) with eigenvalue 2.20 accounted for 43.99% of total variance, a second factor (F2) accounted for 8.90% of variance, for a cumulative variance of 52.89%. Only F1 exceeded Kaiser's criterion of an eigenvalue > 1, meaning that the five demand-driver variables are fairly similar and represent one underlying construct – overall FMCG demand propensity. The most positive loadings for F1 were given to the variables Income Effect (0.828) and Availability (0.794), followed by Price Sensitivity (0.677), Promotions (0.579) and Seasonality (0.300). The communalities ranged from 0.301 (Seasonality) to 0.815 (Income Effect), suggesting that the extracted factor is best explained by Income Effect and Availability is the factor that has the most variance unique to it. Cronbach's Alpha values of 0.754 for the overall scale and 0.797 for F1, which are greater than the commonly accepted value of 0.70, indicate that the five variables are reliable enough to be used in regression analysis.

4.3 Correlation Analysis

	Seasonality	Promotion	Price Sensitivity	Availability	Income Effect
Seasonality	1				
Promotion	0.314	1			
Price Sensitivity	0.252	0.388	1		
Availability	0.179	0.470	0.523	1	
Income Effect	0.090	0.354	0.557	0.679	1

Table 6: Correlation Matrix

The values of the correlation matrix indicate moderate positive relationships between the five demand-driver variables. The highest correlation is between Availability and Income Effect (r = 0.679), followed by Price Sensitivity and Income Effect (r = 0.557) and Availability and Price Sensitivity (r = 0.523), which indicates that price sensitive consumers are also more aware about the availability of products and income effect. The highest correlation is 0.80, which is less than 0.90 and means that multicollinearity is not a problem for the regression model. The remaining variables are correlated with seasonality at the lowest level, with the Income Effect (r = 0.090) strongly supporting the idea that seasonal buying behaviour is not strongly related to the income-driven purchase decision.

4.4 Regression Analysis

Statistic	Value
Multiple R	0.404
R Square	0.163

Statistic	Value
Adjusted R Square	0.123
Standard Error	1.038
Observations	110
F-statistic	4.051
Significance F (p-value)	0.002

Table 7: Regression Statistics

Variable	Coefficient (β)	Standard Error	t-Stat	P-value
Intercept	3.691	0.769	4.797	0.000
Average Seasonality	0.377	0.176	2.143	0.034
Average Promotion	-0.328	0.180	-1.825	0.071
Average Price Sensitivity	-0.005	0.138	-0.038	0.969
Average Availability	-0.080	0.171	-0.468	0.641
Average Income Effect	-0.213	0.120	-1.776	0.079

Table 8: Regression Coefficients

The multiple linear regression model resulted in the R^2 value of 0.163 and Adjusted R^2 value of 0.123 which shows that the five independent variables explain 16.3% of the variation in the monthly spending of FMCG among the respondents. This is moderate level of explanation, but it is in line with the survey type studies of human behaviour which are subject to many factors not measured. The overall model is statistically significant ($F = 4.051$, p value = 0.002), which means that the five demand-driver variables together offer a meaningful prediction of the quantity of the FMCG purchased.

The individual level predictors that were significant were only Seasonality ($\beta = 0.377$, $p = 0.034$) indicating an increase in the monthly spending of FMCG goods for every one-unit increase on the Seasonal demand score on the measurement scale. This reiterates that the festive/special season is the most consistent motivator of the purchase quantity for FMCG among Bengaluru consumers. The coefficient for promotions was negative ($\beta = -0.328$, $p = 0.071$) but was not statistically significant, which may be a result of a decrease in purchasing following the promotions. Price Sensitivity ($\beta = -0.005$, $p = 0.969$), Availability ($\beta = -0.080$, $p = 0.641$), and Income Effect ($\beta = -0.213$, $p = 0.079$) were not statistically significant at the 0.05 level.

4.5 ANOVA

Source	df	SS	MS	F	Significance F
Regression	5	21.818	4.364	4.051	0.002

Source	df	SS	MS	F	Significance F
Residual	104	112.036	1.077		
Total	109	133.855			

Table 9: ANOVA Results

The overall regression overall F statistic is 4.051 at a significance value of 0.002, which is well below the 0.05 threshold, and confirms the overall statistical significance of the regression model. The regression sum of squares (21.818) is similar to the R^2 listed in Section 4.4, accounting for approximately 16.3% of the total sum of squares (133.855).

4.6 Hypothesis Testing Summary

The seasonal or festive demand effect (H_{01}/H_{11}) was found to be significant with a p value of $0.034 < 0.05$. Hence the null hypothesis is rejected and H_{11} is accepted: festive and seasonal factors affect the quantity of FMCG products purchased among consumers of Bengaluru.

The p-value for the promotional offer influence variable (H_{02}/H_{12}) was 0.071, which was not less than the 0.05 value. The null hypothesis is therefore not rejected and H_{12} is not supported: there is no significant difference in the frequency of consumers in this sample purchasing FMCG products because of promotional offers.

The price sensitivity and brand switching variable (H_{03}/H_{13}) obtained a p-value of 0.969 which is greater than the accepted value of 0.05. The null hypothesis cannot be rejected and H_{13} is not accepted: Price changes have no significant impact on brand switching behaviour or quantity of purchases, in this sample.

The overall regression model (H_{04}/H_{14}) was statistically significant ($p = 0.002$; < 0.05). The null hypothesis is rejected, and H_{14} is accepted: A predictive model of the FMCG demand using regression analysis based on variables related to consumer purchase patterns is significant.

5. FINDINGS AND DISCUSSION

5.1 Key Findings

A total of 110 respondents were targeted from Bengaluru and the data were analysed using descriptive statistics, factor analysis, correlation analysis, multiple regression and ANOVA. The results showed that seasonality was the most important driver of demand with a mean score of 3.93 when compared with the other four variables tested (Promotions had a mean score of 3.70, Availability had a mean of 3.55, Price Sensitivity had a mean of 3.40 and Income Effect had a mean of 3.24). Results of factor analysis indicate that the 5 variables converge on one factor such that the weightage of the dominant factor 43.99% which corresponds to a Cronbach's alpha of 0.797, suggesting that the variables are reliable for a regression analysis as an underlying construct. The correlations ranged from moderate positive interrelationships among the variables (the highest correlation was 0.80) thus eliminating any multicollinearity.

Results revealed that the overall regression model was statistically significant as there was 16.3% (Adjusted $R^2 = 0.123$, $F = 4.051$, $p = 0.002$) variation in the monthly FMCG spending due to the five independent variables taken together. Promotions was a predictor on the verge of significance; Price Sensitivity was not statistically significant; and Availability and Income Effect were not statistically significant, but went in the opposite direction ($\beta = -0.328$, $p = 0.071$).Availability and Income Effect were not statistically significant, but had the opposite effect ($\beta = -0.328$, $p = 0.071$); Price Sensitivity was not statistically significant; and seasonality was the only individual factor to reach significance ($\beta = 0.377$, p

= 0.034). The results of the hypothesis testing indicated: H11: supported, H12: unsupported, H13: unsupported and H14: supported (overall predictive model)

5.2 Discussion

The consistency of seasonality being the dominant and only structurally important individual demand driver, matches that had been found by both Sen and Chaudhuri (2017) and Bartwal et al. (2024), which concluded seasonality is an important driver of FMCG demand both structurally and statistically. Everything now supports the argument from the research gap on how festival season determines measurable and survey-measurable demand impacts that cannot be ignored or considered as survey noise but deserve to be made explicit in demand forecasting models.

A lack of significance results from Promotions, Price Sensitivity, Availability and Income Effect does not mean that these factors are unimportant as a driver of monthly FMCG spending in general for the urban consumers of Bengaluru surveyed in this study; but rather that they were not as important as the necessity drivers or seasonal cycles. This interpretation is confirmed by the descriptive findings with household needs and necessity as the top factor for FMCG purchases, accounting for 43 out of 110 respondents, which is much over the number representing discounts (25 respondents) and festive seasons (19 respondents) respectively.

The $F = 4.051$, $p = 0.002$ indicates that the overall regression model is statistically significant; although the R^2 of the model is moderate (0.163), this type of data collected via a simple survey instrument can be used to develop a statistically valid demand forecasting model. The moderate explanation is in line with the fact that there are other factors affecting the purchasing behaviour of man besides the five variables measured in this study. Combined with the survey results, they suggest an actual need for consumer-side survey information as a low-cost and interpretable supplement to the transaction-side forecasting technique, especially for smaller and mid-sized FMCG manufacturers who may not have access to the level of transaction detail to help with the forecasting process.

6. CONCLUSION

6.1 Summary

This study was done to find out what makes people in Bengaluru buy Fast Moving Consumer Goods or FMCG for short every month. The study also wanted to see if a simple model could predict how much FMCG people will buy. The study asked 110 people in Bengaluru some questions. Got some useful answers. It found out that people buy FMCG during festivals and special seasons. This means that FMCG companies should plan ahead for these times. The study also found out that the model it used to predict FMCG sales is a one.

6.2 Recommendations

FMCG companies in Bengaluru should make a plan for festivals. Since people buy FMCG during festivals companies should get ready for these times by planning their supplies and marketing ahead of time. They should also think about how much they spend on promotions. The study found out that promotions do not make people buy FMCG so companies might want to spend their money on something else. The study also shows that asking people questions is a way to find out what they want. This can help FMCG companies predict sales without spending much money. The study should be done again in cities and with different types of people to see if the results are the same.

This analysis is important for FMCG companies. They should use this information to make plans for the future. The study can help them understand what people want and when they want it. This can help FMCG companies make money and be more successful. FMCG companies should also think about combining the results of this study with data to get a better picture of what people want.

6.3 Limitations

The study only asked 110 people in Bengaluru some questions, which's not enough to know what all people in Bengaluru want. The study also relied on people remembering what they bought which might not be accurate. The study only looked at people in Bengaluru so the results might not be the same in cities. The study did not look at what FMCG companies can do to make more products available which can also affect sales.

6.4 Scope for Future Research

Studies should be done to see if the results are the same in other cities and with different types of people. Researchers could also use data like sales data to get a better picture of what people want. This can help FMCG companies make plans and be more successful. The study can be improved by asking more people questions and using advanced statistical methods. This can help FMCG companies understand what people want and make money. FMCG companies should use this information to make plans, for the future. They should also think about how they can use the results of this study to improve their sales and be more successful

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