



An Empirical Investigation into Seasonal Demand and Revenue Variability at Multiple Super markets in Guntur

Veerapaneni Akhil¹, M. Raja Pavan Kumar²

¹ III BBA – Business Analytics, KL Business School, Koneru Lakshmaiah Education Foundation

² Assistant Professor, KL Business School, Koneru Lakshmaiah Education Foundation, Vaddeswaram Campus, Guntur District, A.P.

DOI : <https://doi.org/10.55248/gengpi.07.1026.3258>

ABSTRACT

This study examines seasonal demand and revenue variability across supermarkets in Guntur, Andhra Pradesh. Organised retail in semi-urban India is exposed to festival seasons, agricultural income cycles, wedding seasons and school reopening, which make revenue fluctuate through the year. Using a descriptive, cross-sectional, quantitative design, the study analyses primary questionnaire data from 115 consumers through percentage analysis, a Seasonal Demand Index (SDI) and six chi-square tests. Of the respondents, 93.9% spend more during festivals and special occasions, by about 22.5% on average (plausible range 14.4%–30.8%) ($\chi^2 = 92.78$, $p < 0.001$). Sankranti, Dasara and Diwali are named by 69.6% as the most influential occasions ($\chi^2 = 24.57$, $p < 0.001$), although the share of respondents raising purchases does not differ significantly across the five seasons and occasions ($\chi^2 = 3.74$, $p = 0.44$); festivals nevertheless record the highest SDI (135, where 100 is average). Discounts and promotions are named by 37.4% as the biggest driver of changes in sales ($\chi^2 = 33.30$, $p < 0.001$). Older respondents report larger festival-time increases ($p = 0.008$), although this is not significant among Guntur residents alone, while satisfaction does not differ significantly across supermarket types. Overall, 49.6% are satisfied or very satisfied with supermarkets' ability to meet higher demand and 11.3% are dissatisfied. The paper recommends festival-calendar-based inventory planning, deliberate promotion planning and close monitoring of product availability.

Keywords: seasonal demand, revenues, grocery retail, seasonal variations, supermarkets, festival spending, consumer behaviour, Guntur, chi-square test

1. Introduction

Organised retail has experienced a boom of the last two decades in metros but also in Tier-2 cities like Guntur in Andhra Pradesh. The revenue of supermarkets is not uniform throughout the year, it depends on regional festivals, income levels of the people, which would largely depend on the crop and agricultural income, wedding season, reopening of schools, etc. Knowledge of such demand pattern helps managers to stock the right amount, avoid stock-out and stock excess and control labour costs. The present study tries to identify the season-wise demand pattern and its effect on the revenue of a number of supermarkets using primary data.

Problem statement. While demand based on seasonality has been examined in organised retail, it has been limited to a handful of categories or large metro settings. No comprehensive research exists that measures changes in revenue across a collection of supermarkets within a regional centre and reveals its causes, and retailers with a national approach cannot treat all local stocks the same.

Objectives and questions. The aims: (O1) to detect seasonal demand in various supermarkets; (O2) to examine variation of revenue within various periods; (O3) to find factors influencing demand; (O4) to examine seasonal demand and revenue variation between supermarkets; and (O5) to create appropriate inventory and revenue controls. The research questions are similar: what kinds of seasonal patterns are there, how much revenue varies between time periods, what factors could influence demand, whether there are differences in seasonal patterns of demand and revenue between supermarkets, and how managers could use the results.

Scope and significance. The present study is confined to the supermarkets of Guntur city and is limited to seasonal variation in demand, variations in sales and income and reasons thereof. This study is useful for the managers to take decisions on pricing, inventory, and staffing involved in the seasonal fluctuation of demand and for other studies on organised retail.

2. Review of Literature and Research Gap

Raguraman (2013) used association rule mining on twelve thousand transactions and found that weather, local festivals, and socio-economic changes Really influence buying behaviour, with products like juices, spice mixtures, and mosquito repellents showing notable seasonal demand. The study focused on a single supermarket in Kanchipuram and did not account for week-to-week variation. Jeyachandran (2019) compared traditional stores and

supermarkets among Indian retail customers, finding that buying behaviour is influenced by age, gender, and employment, but the research was limited to Chennai. Dharani and Praveen (2023) found that consumers consider price, ratings, and reviews, that just over half were satisfied with supermarket amenities, and that satisfaction is driven by brand image, word of mouth, service, and quality; still, the study used a single-institution sample and did not consider online influences, limiting its generalisability. Ranjan and Singh (2025) analysed secondary data from D-Mart, V-Mart, and Best Price in Bhopal and found that assortment, competitive pricing, atmospherics, and promotions affect behaviour and satisfaction, but did not examine seasonality. Shetye (2026) applied market basket analysis at D-Mart to identify products purchased together for placement, promotion, and inventory strategies, without considering personalised digital marketing.

Research gap. Previous work indicates that consumer behaviour and consumer satisfaction have an effect on supermarket revenue, seasonality has an effect on demand, and association rule mining can be used to examine buying behaviour. The bulk of the previous research deals with one store or location, and considers either satisfaction or buying behaviour, not revenue; and no previous research considers how revenue varies with seasonality across multiple supermarkets in one city. This research aims to fill this gap.

3. Hypotheses of the Study

Six null hypotheses (H_0), each linked to an objective, are tested; the alternative (H_1) in every case is that H_0 is false. They are: **H1** (O1): respondents are equally spread across the five seasons/occasions in which they increase purchases; **H2** (O1): the six festivals/occasions are equally influential; **H3** (O2): the five classes of festival-time increase in spending are equally likely; **H4** (O2): the festival-time increase is independent of age group; **H5** (O3): the five factors are equally likely to be named the biggest cause of changes in sales; and **H6** (O4): satisfaction with supermarkets' ability to meet increased demand is independent of the preferred type of supermarket. Because the survey records consumers' own reported spending, "revenue" here means reported expenditure (Section 4.1). All tests use the 5% level of significance and H_0 is rejected when $p < 0.05$. As six tests are run on one data set, Holm-adjusted p-values are also reported. "Do not reject H_0 " means the sample gives insufficient evidence against H_0 , not that H_0 is accepted.

4. Research Methodology

4.1 Research design

This descriptive, cross-sectional, and quantitative study is founded on a consumer questionnaire (Kothari, 2004). Each respondent answered once and specified typical spendings by season and occasion. I have no sales ledger data of revenue variation at store level, and so it is estimated on the demand side: reported frequency of visits, average spendings per visit and proportionate festival-time uplift are used to approximate change in typical customer spendings between low- and high-demand seasons. These figures are based on recall and perception; they are not validated store income.

4.2 Sample design

The target population is consumers who shop at supermarkets in Guntur and neighbouring centres in its catchment; the sampling unit is an individual consumer. No sampling frame exists, so non-probability convenience sampling was used, giving 115 complete questionnaires with no missing values: Guntur 82 (71.3%), Vijayawada 11, Tenali 8, Mangalagiri 6 and other places 8. Ages are 18–21 (60), 21–26 (35) and 26–35 (20). If the sample were random, the margin of error for a proportion would be at most ± 9.1 percentage points at 95% confidence (± 10.8 for the Guntur-only sample). All tests were rerun on Guntur residents to check consistency with the stated scope.

4.3 Data collection and questionnaire preparation

Primary data was obtained through a questionnaire of 13 closed questions; no names or contact details were gathered. There are four sections, each aligned with an objective: (A) respondent profile (age group, city); (B) shopping behaviour (visit frequency, expenditure per visit, preferred supermarket type); (C) seasonal demand and expenditure (season/occasion of increased purchases, most influential festival, magnitude of festival-time increase, product category bought in greater quantities); and (D) store response and key sales drivers (switching for offers, availability changes, satisfaction with meeting increased demand, biggest factor behind sales changes). Closed questions decrease the possibility for coding error and allow chi-square testing; expenditure was recorded in class intervals to make the sensitive question easier. Content validity is secured by ensuring all questions relate to an objective; since all measures are single-item, internal reliability (Cronbach's alpha) cannot be computed. Secondary data come from the studies reviewed in Section 2.

4.4 Derived measures and tools of analysis

Responses were coded as categories, and class midpoints were used for numerical summaries. Estimated monthly spend (MS) = visits per month $\times$ spend per visit, with visits per month assumed as 30 (daily), 10 (2–3 times a week), 4 (once a week), 2.5 (2–3 times a month) and 1 (rarely), and spend per visit at class midpoints (₹250, 750, 1,500, 2,500 and 3,500 for "above ₹3,000"). The festival-time increase (U) uses midpoints of 0, 5, 17.5, 38 and 60 for "no increase", "less than 10%", "10–25%", "26–50%" and "more than 50%"; lower- and upper-limit assumptions bracket the mean (the open class is capped at 75%). The spend-weighted increase is $\Sigma(\text{MS} \times \text{U}) / \Sigma \text{MS}$. The Seasonal Demand Index for category j is $\text{SDI}_j = (n_j / N) \times k \times 100$,

where n_j is the number naming category j , $N = 115$ and k is the number of categories; 100 is average, and the spend-weighted version replaces n_j with the total MS of those naming j .

Analysis uses frequencies, percentages, medians and quartiles with bar graphs, pie charts and box plots. Hypotheses are tested with the chi-square goodness-of-fit test, $\chi^2 = \sum (O - E)^2 / E$ with $E = n / k$ (H1, H2, H3, H5), and the chi-square test of independence, with $E = (\text{row total} \times \text{column total}) / n$ (H4, H6) (Pearson, 1900). Effect sizes are Cramér's V (1946) and Cohen's w (1988), adjusted standardised residuals (Haberman, 1973; absolute values above 1.96 are significant) show which cells depart from expectation, and Wilson confidence intervals (1927) and the Holm adjustment (1979) are used for a proportion and for multiple tests. Data were compiled in MS Excel and analysed in Python (pandas, SciPy, Matplotlib).

Assumptions and power. Following Cochran (1954), at least 80% of cells need expected counts of 5 or more and none below 1. After grouping, the age test (H4) meets this rule; for H6 the p -value comes from Monte Carlo simulation (20,000 random tables with fixed margins). With $N = 115$, the five-category goodness-of-fit test has about 73% power to detect a medium departure from equal shares ($w = 0.30$) and 37% for a small one ($w = 0.20$), so a non-significant result means “no clear evidence of a difference”, not “no difference”.

5. Data Analysis

Percentages are based on $N = 115$ unless stated. Sections 5.1–5.5 present results and test the hypotheses; Section 5.6 summarises all tests and reports a robustness check.

5.1 Profile of respondents and shopping behaviour

The sample is young: 82.6% are aged 18–26 (52.2% aged 18–21), and 71.3% live in Guntur, with the rest in Vijayawada (9.6%), Tenali (7.0%), Mangalagiri (5.2%) and other places (7.0%) (Figure 1). Shopping is frequent but baskets are moderate: 73 respondents (63.5%) visit at least weekly and 14 (12.2%) rarely; the most common spend per visit is ₹500–1,000 (45.2%), 62.6% spend up to ₹1,000 and 16.5% spend more than ₹2,000. Large supermarkets are preferred by 37.4%, medium-sized by 27.0%, local by 20.0% and chains by 15.7% (Figure 2). Estimated monthly spend is strongly right-skewed (median ₹3,000, inter-quartile range ₹1,875–7,500, mean ₹7,118, maximum ₹75,000), so medians are used for comparisons.

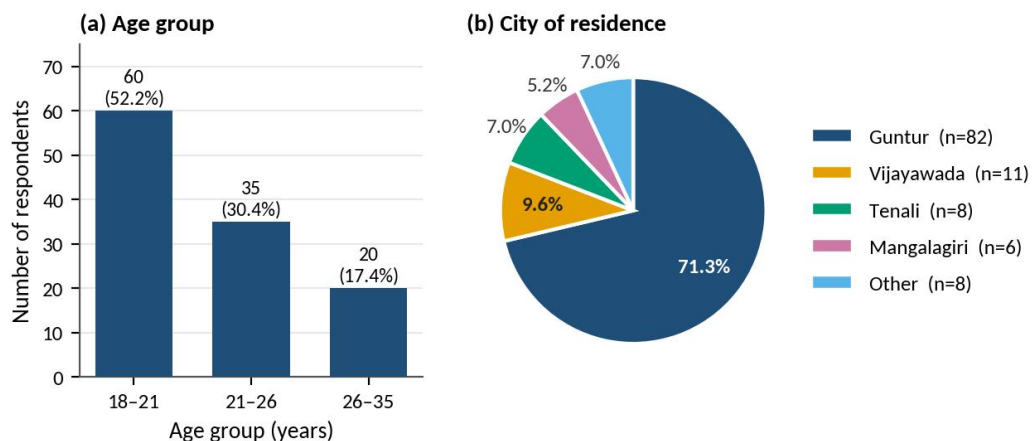


Figure 1: Age group and city of residence of respondents (N = 115)

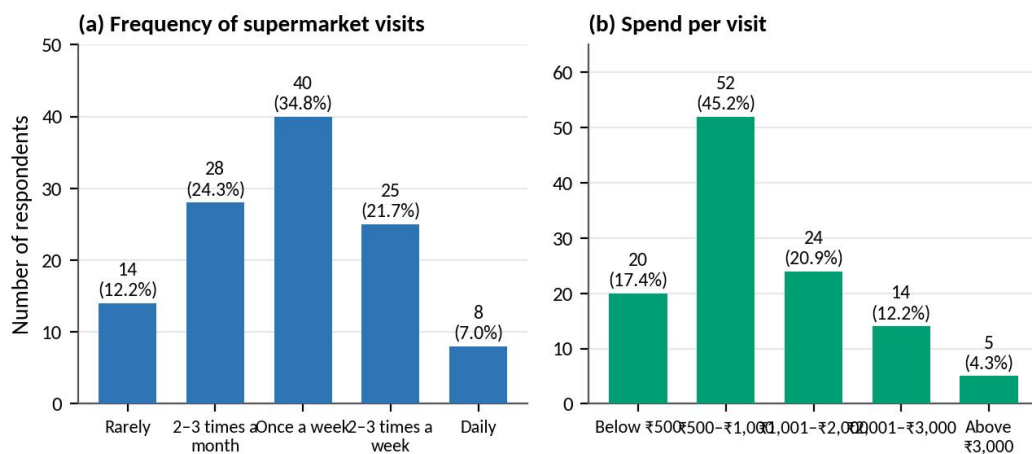


Figure 2: Frequency of supermarket visits and spend per visit

5.2 Seasonal demand pattern (H1, H2)

Festivals are the most frequent answer for when respondents raise purchases (27.0%), followed by summer (20.0%), school/college reopening (18.3%), and winter and monsoon (17.4% each) (Table 1, Figure 3). The head-count SDI is highest for festivals (135) and lowest for winter and monsoon (87); on the spend-weighted basis festivals (146) and summer (148) lead. Removing the two highest spenders raises the festival index to 172 and lowers summer to 120, so the festival lead is robust while summer's rank rests on a few heavy spenders. **H1:** $\chi^2 = 3.74$, $df = 4$, $p = 0.442$, Cohen's $w = 0.18$; do not reject H_0 . No season is named significantly more or less often than expected.

Table 1: Season/occasion of increased purchases and Seasonal Demand Index (N = 115)

Season/occasion	n	%	Std. residual	SDI	Spend-weighted SDI
Festivals	31	27.0	+1.67	135	146
Summer	23	20.0	0.00	100	148
School/college reopening	21	18.3	-0.42	91	80
Winter	20	17.4	-0.63	87	51
Monsoon	20	17.4	-0.63	87	74

Expected = 23.0 per category under equal shares. SDI: 100 = average.

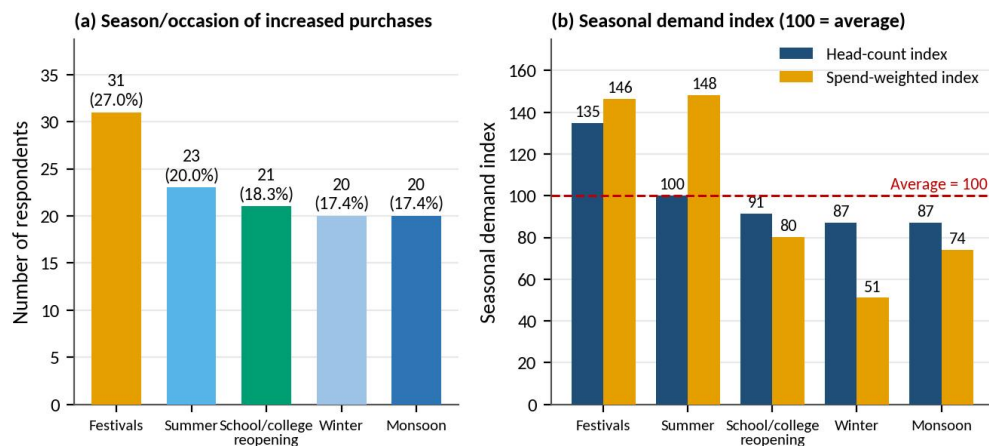


Figure 3: Season/occasion of increased purchases (a) and Seasonal Demand Index (b)

Sankranti (28.7%), Dasara (22.6%) and Diwali (18.3%) together are named by 69.6% as the most influential occasion, followed by weddings/functions (15.7%), Ugadi (7.8%) and Christmas (7.0%) (Figure 4); their head-count SDIs are 172, 136, 110, 94, 47 and 42. **H2:** $\chi^2 = 24.57$, $df = 5$, $p < 0.001$, $w = 0.46$; reject H_0 . Sankranti (residual +3.16) is named significantly more often than expected, and Ugadi (-2.32) and Christmas (-2.55) less often.

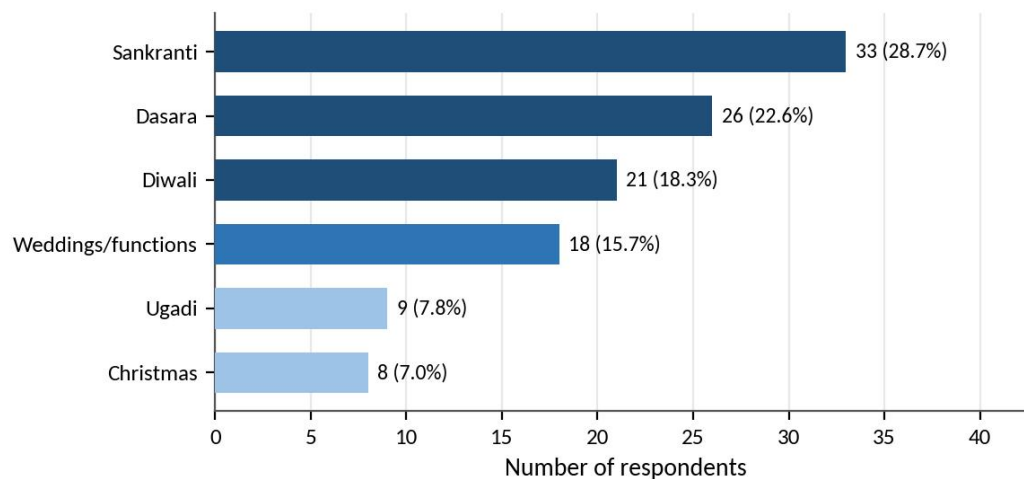


Figure 4: Festival/occasion with the greatest influence on supermarket purchases

5.3 Variation in spending during festivals (H3, H4)

Only 7 respondents (6.1%) report no festival-time increase; the modal class is 10–25% (52.2%) and 31.3% spend more than 25% extra, so 93.9% spend more than usual (95% Wilson interval 88.0%–97.0%) (Figure 5). **H3:** $\chi^2 = 92.78$, $df = 4$, $p < 0.001$, $w = 0.90$; reject H_0 . The 10–25% class is far more frequent than expected (residual +7.72). The simple mean increase is 22.5% (14.4% using lower class limits, 30.8% using upper limits) and 22.7% when weighted by spending, so heavy and light shoppers raise spending by similar proportions; average monthly spending rises from ₹7,118 to ₹8,732 in a festival month. The increase is similar across festivals: the median is 17.5% for each, and means range only from 20.5% to 25.2%.

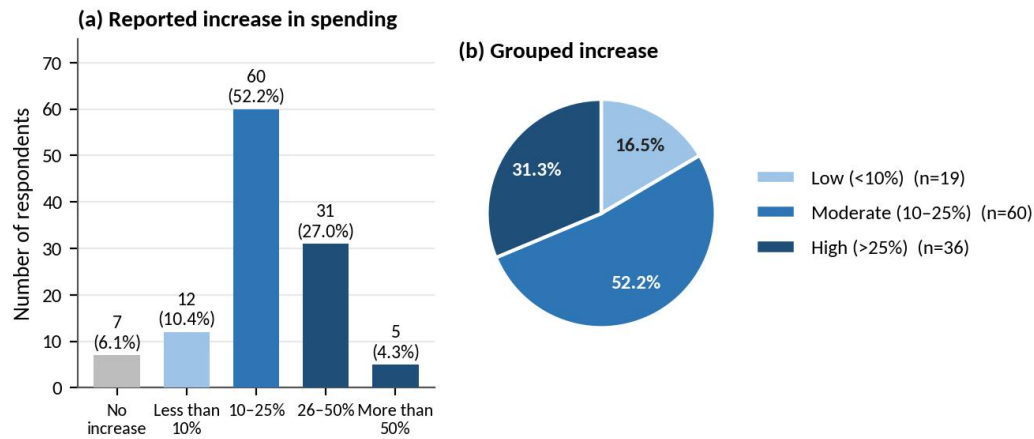


Figure 5: Reported increase in spending during festivals/special occasions (a) and grouped increase (b)

The share reporting a high increase (above 25%) rises with age: 16.7% for ages 18–21, 42.9% for 21–26 and 55.0% for 26–35 (Table 2). **H4:** $\chi^2 = 13.66$, $df = 4$, $p = 0.008$, Cramér's $V = 0.244$; reject H_0 . Respondents aged 18–21 are under-represented in the high-increase group (adjusted residual –3.54) and those aged 26–35 over-represented (+2.51). The result survives Holm adjustment for the six tests ($p = 0.026$) but is not significant in the Guntur-only sample ($p = 0.093$, $V = 0.22$), so it should be read with caution.

Table 2: Age group and grouped festival-time increase: n (row %)

Age group	Low (<10%)	Moderate (10–25%)	High (>25%)	Total
18–21 years	13 (21.7%)	37 (61.7%)	10 (16.7%)	60
21–26 years	4 (11.4%)	16 (45.7%)	15 (42.9%)	35
26–35 years	2 (10.0%)	7 (35.0%)	11 (55.0%)	20
All respondents	19 (16.5%)	60 (52.2%)	36 (31.3%)	115

Low = “no increase” and “less than 10%”; High = “26–50%” and “more than 50%”.

5.4 Products, store response and factors behind sales changes (H5)

Snacks and sweets are the most commonly bought food category during the seasonal period (32.2%), followed by groceries (20.0%), clothing/personal care (15.7%), household products (13.0%), drinks (10.4%) and fruit and veg (8.7%) (Figure 6). Responses from stores are generally mixed: 84.3% change supermarket at least sometimes for seasonal offers (35.7% often or always) and 87.8% see variation in product availability at least sometimes (33.9% often or frequently); 49.6% satisfied or very satisfied with supermarkets' ability to meet demand for products, 39.1% neutral and 11.3% dissatisfied (Figure 7).

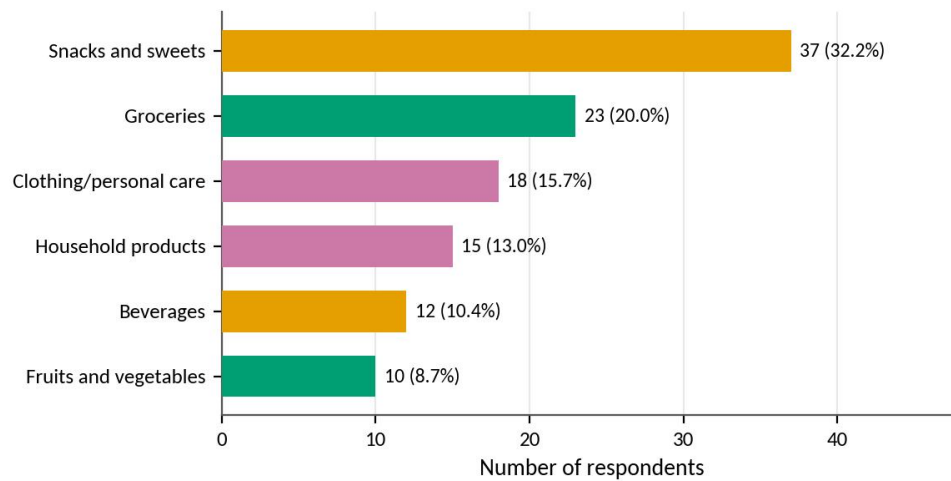


Figure 6: Product categories bought more in seasonal and festival periods

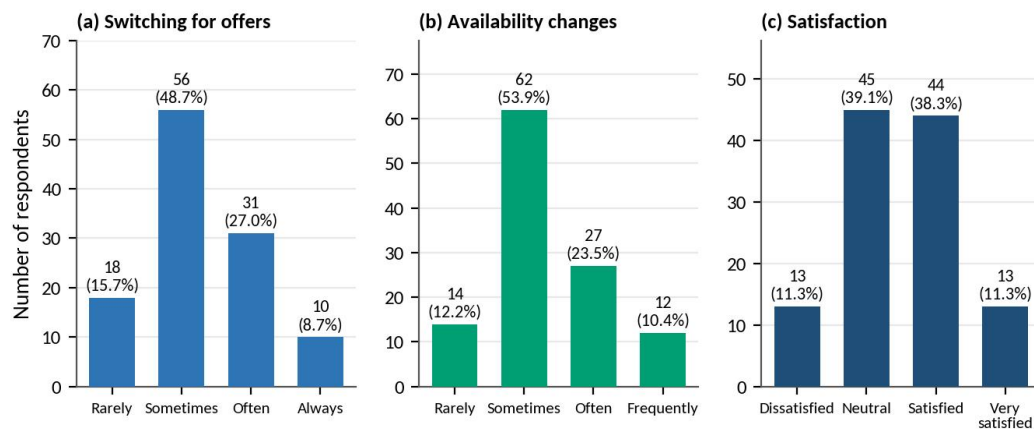


Figure 7: Switching for seasonal offers (a), noticed changes in product availability (b) and satisfaction with meeting increased demand (c)

Discounts and promotions are the most cited biggest factor behind sales changes (37.4%), followed by inflation/prices (26.1%), customer income (18.3%), weather/season (9.6%) and festivals (8.7%) (Figure 8); price-related factors together account for 63.5%. **H5:** $\chi^2 = 33.30$, $df = 4$, $p < 0.001$, $w = 0.54$; reject H_0 . Discounts (residual +4.17) are named more often than expected, weather/season (-2.50) and festivals (-2.71) less often.

(a) Biggest factor behind changes in sales



Figure 8: Biggest factor behind changes in supermarket sales/revenue

5.5 Comparison across supermarket types and relationships among variables (H6)

Chain customers stand out descriptively (Table 3, Figure 9): median monthly spend of ₹7,500 against ₹3,000 for the other types, a mean increase of 28.4% against 18.8%–23.5%, and the lowest satisfaction (33.3% against 44.2%–64.5%). These differences rest on only 18 chain respondents and were

not tested formally. **H6:** $\chi^2 = 6.54$, $df = 6$, Monte Carlo $p = 0.373$, $V = 0.169$; do not reject H_0 . Satisfaction with meeting increased demand does not differ significantly across the four supermarket types.

Table 3: Profile of respondents by preferred type of supermarket

Preferred type	n	Median monthly spend	Mean festival increase (%)	Festivals as main season (%)	Satisfied / very satisfied (%)
Local supermarket	23	₹3,000	18.8	30.4	52.2
Medium-sized supermarket	31	₹3,000	20.4	32.3	64.5
Large supermarket	43	₹3,000	23.5	25.6	44.2
Supermarket chain	18	₹7,500	28.4	16.7	33.3
All respondents	115	₹3,000	22.5	27.0	49.6

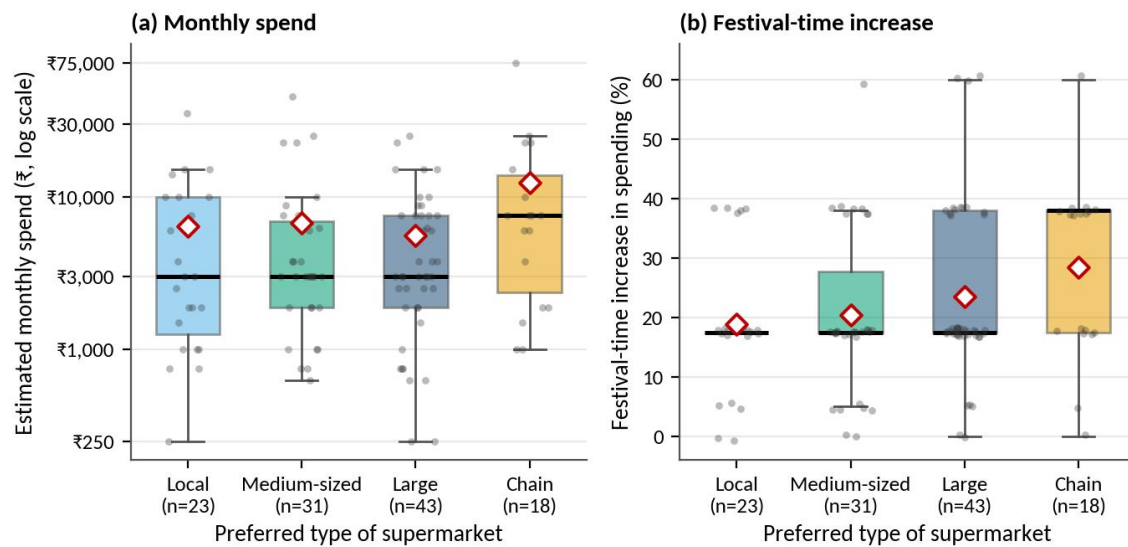


Figure 9: Estimated monthly spend (a) and festival-time increase in spending (b) by preferred type of supermarket (diamonds mark means)

Descriptively, visit frequency and spend per visit show no visible relationship (Figure 10): mean spend per visit stays between ₹929 and ₹1,330 across visit-frequency levels, and the mean festival-time increase stays between 21.6% and 23.9% across quartiles of monthly spend. Differences in monthly spend therefore arise mainly from how often customers visit, and light and heavy spenders raise spending in similar proportion.

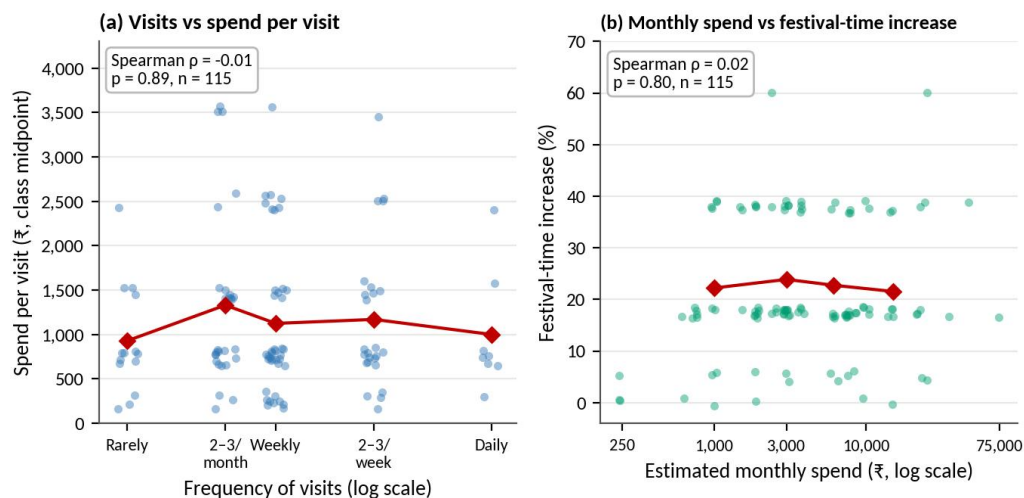


Figure 10: Visits and spend per visit (a) and monthly spend and festival-time increase (b); the red line joins the mean at each level (a) and for each quartile (b)

5.6 Summary of hypothesis tests and robustness check

Four of the six nulls are rejected at the 5% level (H2, H3, H4, H5) and all four remain significant after Holm adjustment (Table 4). H1 and H6 are not rejected.

Table 4: Hypotheses, tests and results (N = 115)

No.	Null hypothesis (H ₀)	Test	Statistic	p (Holm p)	Decision
H1	Respondents are equally spread across the five seasons/occasions of increased purchases	χ^2 GOF	$\chi^2 = 3.74$	0.442 (0.746)	Do not reject
H2	The six festivals/occasions are equally influential	χ^2 GOF	$\chi^2 = 24.57$	<0.001 (0.001)	Reject
H3	The five classes of festival-time increase are equally likely	χ^2 GOF	$\chi^2 = 92.78$	<0.001 (<0.001)	Reject
H4	Festival-time increase is independent of age group	χ^2 indep.	$\chi^2 = 13.66$	0.008 (0.026)	Reject
H5	The five factors are equally likely to be named the biggest cause of sales changes	χ^2 GOF	$\chi^2 = 33.30$	<0.001 (<0.001)	Reject
H6	Satisfaction is independent of supermarket type	χ^2 indep.	$\chi^2 = 6.54$	0.373‡ (0.746)	Do not reject

GOF = goodness-of-fit; indep. = test of independence. ‡ Monte Carlo p-value because Cochran's rule was not met.

Robustness (Guntur residents only, n = 82). The conclusion is the same for five of the six tests H2, H3, and H5. The exception is H4, not significant for Guntur residents ($p = 0.093$, $V = 0.22$ as against 0.24 in the full sample), and the pattern by age because of this remains tentative and takes confirmation in a larger sample.

6. Interpretations

Seasonal demand (O1). Festivals form the largest single peak (27.0%; SDI 135), and Sankranti (mid-January) together with Dasara and Diwali (September–November) gives two main festival peaks a year; weddings and functions matter to 15.7%. But no peak is statistically dominant (H1, $p = 0.44$): 54.8% name a weather season and 18.3% school reopening, so demand peaks are spread through the year and festivals add a further, smaller one. With 73% power for a medium effect, a small festival advantage cannot be ruled out. The importance of festivals agrees with Raguraman (2013), who found that weather, festivals and socio-economic changes influence buying behaviour.

Revenue variation (O2). Increases are near-universal but moderate: for every ₹100 a typical customer spends in a normal month, about ₹123 is spent in a festival month. The size of the increase is similar across festivals, so their cash impact depends mainly on how many customers they move (H2), which is why Sankranti, Dasara and Diwali deserve most planning attention. Larger increases among older respondents (H4) may reflect larger households and more festival food, gifts and hospitality, a conjecture this study cannot test; the direction is consistent with Jeyachandran (2019), but the result does not hold in the Guntur-only sample. All percentages are consumer-reported, not audited store sales.

Factors affecting demand (O3). Price and promotion dominate (63.5%, H5), consistent with Ranjan and Singh (2025); consumers may experience the festival effect largely through festival offers. Shoppers are not tied to one store (84.3% switch at least sometimes), so competition for the festival basket is intense. Snacks, sweets and groceries lead the seasonal basket, echoing Raguraman's (2013) product-level seasonality.

Supermarket types (O4). Satisfaction does not differ significantly by supermarket type (H6), and seasonal demand appears broadly market-wide, so a common Guntur template calibrated to each store's sales history seems workable. The higher spend, larger increase and lower satisfaction of chain customers hint at operational pressure at chains, but with 18 respondents this is a lead, not a conclusion.

Inventory and revenue controls (O5). Only 49.6% are satisfied with supermarkets' ability to meet higher demand (similar to the just-over-half reported for amenities by Dharani and Praveen, 2023); the large neutral group (39.1%) is the main opportunity. Availability changes are widely visible (87.8%), so stock-outs and overstocking are noticed by customers at peak times.

Contribution. The study offers consumer-based evidence for Guntur across several supermarkets, building on Raguraman (2013), Jeyachandran (2019), Dharani and Praveen (2023) and Ranjan and Singh (2025), and complementing Shetye (2026). The research gap is closed only partly, because revenue is consumer-estimated rather than drawn from store ledgers.

7. Findings, Suggestions and Conclusion

7.1 Findings

1. Festivals are named most often for raising purchases (27.0%; SDI 135), but the five seasons/occasions do not differ significantly ($H1: p = 0.44$).
2. Sankranti (28.7%), Dasara (22.6%) and Diwali (18.3%) are named by 69.6% as most influential; Ugadi (7.8%) and Christmas (7.0%) matter least ($H2: p < 0.001$).
3. 93.9% spend more during festivals and special occasions; the average increase is about 22.5% (14.4%–30.8%), or 22.7% spend-weighted, and the most common increase is 10–25% ($H3: p < 0.001$).
4. Older respondents report larger increases ($H4: p = 0.008$; Holm $p = 0.026$), but the pattern is not significant among Guntur residents alone ($p = 0.093$).
5. Discounts and promotions (37.4%) and inflation/prices (26.1%) are seen as the biggest drivers of sales changes ($H5: p < 0.001$). Snacks and sweets (32.2%) and groceries (20.0%) are bought more in seasonal periods.
6. Satisfaction does not differ significantly across supermarket types ($H6: p = 0.37$); chains show the highest average increase (28.4%) and lowest satisfaction (33.3%) descriptively.
7. 84.3% change supermarket at least sometimes for seasonal offers and 87.8% notice availability changes; 49.6% are satisfied, 39.1% neutral and 11.3% dissatisfied.
8. Restricting the analysis to Guntur residents leaves five of six decisions unchanged, including H2, H3 and H5.

7.2 Suggestions

The suggestions are addressed to supermarket managers in Guntur and should be adapted with each store's own sales data.

1. Line up festival calendar for plan inventory Sankranti, Dasara, and Diwali are at 69.6% of customers; forecast volume during peak periods about 14%–31% above the normal month (centered on approximately 23%) on store sales.
2. Organise categories first. Fill your pantry and snacks sweets before groceries; fill your clothing/personal care and household stocks with care to avoid shortfalls and over-ordering.
3. Maintain a rolling calendar. Include summer, monsoon, winter, and school or college reopening periods with festival peaks, as no single season is clearly dominant.
4. Focus on schedule and tracking promotions. Launch key offers during the three most important festivals, keep track of incremental sales, and use price match/loyalty offers to keep customers from switching.
5. Protect availability and satisfaction Measure stock-out days in festival weeks, agree safety stock with suppliers, prepare substitutes and work on turning the 39.1% neutral customers into satisfied customers.
6. Match staffing to peaks. When festival weeks are supplemented with replenishment and billing staff and quiet weeks have fewer staff, balance service and labour cost.
7. Segments to focus on. Festival hampers, bulk, and function packs for 21–35 year olds, low cost bundles for the youngest shoppers; these are the beginning to test.
8. Validate a Guntur template by using the same one. Adjust a common seasonal template for each store and compare it to the seasonal indices of the monthly point-of-sale revenue (for example ratio-to-moving-average) for the reported 22.5% increase.

7.3 Conclusion

Based on a survey of 115 customers, this paper examined demand and revenue shifts through the shopping year at Guntur's supermarkets from the consumer side. Demand lifts are nearly universal (93.9% spend more at festivals and special occasions) and moderate (average 22.5%, range 14.4%–30.8%). They centre on Sankranti, Dasara and Diwali, named by 69.6%, although the five seasons and occasions attract statistically similar shares of respondents, so demand lifts are spread through the year. Consumers see prices and promotions as stronger drivers than weather or festivals as such. Satisfaction does not differ significantly between supermarket types, supporting a citywide seasonal template, with only suggestive differences for older consumers.

For managers, the practical message is to plan stock, promotions and staffing on a festival calendar with a 14%–31% working range above normal-month volumes, ensure availability at peaks and convert neutral customers into satisfied ones. For research, the next step is to confirm these consumer-

reported profiles against month-by-month store revenue and a larger probability sample. The study fills the gap identified in Section 2 by describing consumer-based seasonal variation in supermarket revenue in one regional city, without a direct measure of observed store revenue.

7.4 Scope for further research

Use two to three years of monthly store-level sales to derive seasonal indices and test seasonal models; draw a larger probability sample including income, household size and occupation; use loyalty-card or point-of-sale data to study product-level seasonality and promotion effects; and repeat the study in other Tier-2 towns of Andhra Pradesh.

References

- Cochran, W. G. (1954). Some methods for strengthening the common χ^2 tests. *Biometrics*, 10(4), 417–451.
- Cohen, J. (1988). *Statistical power analysis for the behavioural sciences* (2nd ed.). Lawrence Erlbaum Associates.
- Cramér, H. (1946). *Mathematical methods of statistics*. Princeton University Press.
- Dharani, S. K., & Praveen, S. V. (2023). A study of consumer buying behaviour towards supermarkets.
- Haberman, S. J. (1973). The analysis of residuals in cross-classified tables. *Biometrics*, 29(1), 205–220.
- Holm, S. (1979). A simple sequentially rejective multiple test procedure. *Scandinavian Journal of Statistics*, 6(2), 65–70.
- Jeyachandran. (2019). Grocery shopping pattern of Indian retail customers: Traditional stores vs. supermarkets.
- Kothari, C. R. (2004). *Research methodology: Methods and techniques* (2nd rev. ed.). New Age International Publishers.
- Pearson, K. (1900). On the criterion that a given system of deviations from the probable in the case of a correlated system of variables is such that it can be reasonably supposed to have arisen from random sampling. *Philosophical Magazine, Series 5*, 50(302), 157–175.
- Raguraman. (2013). A seasonal approach for analysis of temporal trends in retail marketing using association rule mining. *International Journal of Computer Applications*, 71(13), 10–15.
- Ranjan, & Singh. (2025). A study on consumer behaviour towards organised retail stores in Bhopal city.
- Shetye. (2026). A study on market basket analysis of consumer buying behaviour with reference to D-Mart.
- Wilson, E. B. (1927). Probable inference, the law of succession, and statistical inference. *Journal of the American Statistical Association*, 22(158), 209–212.