



International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Evaluating the Effectiveness of Business Analytics in Demand Forecasting: A Study of the Inventory Department at Spencer's Retail, Vijayawada

Kota Jaswanth Kumar¹, 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, Green Fields, Vaddeswaram Campus, Guntur District, A.P.

ABSTRACT :

This research investigates business analytics for demand forecasting in the inventory department of Spencer's Retail, Vijayawada. Analytics can contribute to demand forecasting by allowing retailers to use historical sales and current demand information to predict future demand, optimize stock levels, and reduce stockouts and wastage. This research aims to identify the analytics tools and techniques that are used for demand forecasting, to assess their perceived impact on forecast accuracy and inventory management, and to identify the practical implementation issues of using such techniques. A quantitative cross-sectional descriptive study was employed with a structured questionnaire and the resultant analysed data set of 128 records of student respondents, 112 simulated from 16 actual responses this way illustrating the analytical process and indicating trends rather than practice at Spencer's Retail. Respondents expressed an optimistic attitude to analytics, and their perceived usefulness was the primary predictor of predicted demand forecasting results.

Keywords: business analytics; demand forecasting; inventory management; retail; Spencer's Retail; forecast accuracy

CHAPTER 1: INTRODUCTION

1.1 Introduction

In today's competitive retail sector, forecasting customer demand is among the most important indicators of organisational success. Changing consumer needs, seasonality, promotions, and supply chain inconsistencies make demand hard to predict, yet accurate forecasts allow retailers to avoid excess inventory and costly stockouts and to reduce carrying costs. Business analytics supports this by using historical sales data and models to replace intuition-based demand planning with evidence-based inventory planning.

Spencer's Retail, one of India's biggest organised retail chains and one of the hypermarkets, supermarkets, and daily needs stores. As with many other retailers, its inventory department also has to match stock with demand in various product categories. This case study explores how business analytics is used for demand forecasting at the inventory department of a Spencer's Retail outlet at Vijayawada, and perceived effectiveness.

1.2 Problem Statement

While analytics can be promoted as the answer to forecast accuracy, the reality is that the results will be a function of the quality of the data, IT capabilities, human expertise and organisational support. Better inventory department analytics usage should translate into lower inventory costs and more effective operational execution in the quest for accuracy. Is the analytics use today consistent with these accuracy benefits?

1.3 Research Objectives

For analysis of business analytics tools and techniques used in demand forecast in inventory department.

- To assess the impact of analytics on forecast accuracy and the management of inventory.
- To explore the challenges faced in the implementation and utilization of analytics for demand forecasting.

- To evaluate the effectiveness of the analytics in lowering out-of-stock and overstocking occurrences.
- To examine the extent of analytics based forecast adoption by the employees and the perceived accuracy and usability of analytics based forecast and to provide necessary suggestions.

1.4 Research Questions, Scope and Importance

The research questions address the objectives: what analytics are used; how much do they improve forecasting accuracy; what problems are faced in their implementation; do they curb stockouts and overstocking; and how do users perceive their accuracy and utility. The scope is demand forecasting for inventory management only; other functions (marketing finance HR) and other sites of Spencer's are out of scope. The relevance of the study is that forecasting is key to inventory effectiveness and retail profitability, and it offers a platform for subsequent research on analytics in Indian retail.

CHAPTER 2: REVIEW OF LITERATURE

Early studies suggest business analytics is transforming how demand and stock levels are calculated more accurately, driven by data, and raising issues around use, data quality, and integration.

2.1 Earlier Studies

Sharma and Patel (2023) In a survey of inventory and supply chain managers in organized Indian retail chains, we discovered that those firms that employed analytics-driven forecasting experienced a lot lower stockouts and excess inventory than those firms that did not. **Ramesh, Nair and Iyer (2024)** on how retail inventory has matured and how responsive the supply chain is; using 4 predictors: data infrastructure, analytic capability, planning frequency and support of top management and found that organisational support and staff knowledge had the greatest impact on usage. This paper uses similar indicators for perceptions of analytics in a single retail inventory function.

Comparative studies indicate that forecasts based on historical averages or managerial intuition are less adaptable to sudden demand changes than those generated by multivariate analytics that build in seasonality, advertising, and external signals, assuming the historical data is reliable. Dashboards for demand sensing and trend detection can improve reorder accuracy and reduce safety stock, but their effectiveness relies on high-quality sales and inventory data. Since forecasts directly influence ordering and replenishment, staff attitudes toward analytics are also important for successful adoption and training.

2.2 Research Gap

Almost all literature deals with multi-store companies or with retail environments outside of India. Little research exists on analytics within the inventory function of a single retail outlet in a Tier-2 city in India, like Vijayawada. This paper fills that gap.

2.3 Hypotheses of the Study

The following null (H0) and alternative (H1) hypotheses were tested at the 5 per cent level ($\alpha = 0.05$). Composite A is the mean of five items on perceived usefulness of analytics; composite B is the mean of six items on perceived forecasting and inventory outcomes (Section 4.1).

Table 2.1: Hypotheses of the study

No.	Hypothesis (stated as the null, H0)	Test applied
H1	Perception of business analytics is neutral (mean = 3); H1: favourable (mean > 3).	One-sample t-test; Wilcoxon signed-rank
H2	No association between familiarity with analytics and perceived overall effectiveness.	Chi-square (independence)
H3	No association between awareness of Spencer's Retail and belief that analytics can help it predict demand.	Chi-square (independence)
H4	No relationship between perceived usefulness and perceived effectiveness of forecasting outcomes.	Spearman and Pearson correlation
H5	Usefulness and familiarity do not significantly influence overall effectiveness.	Multiple linear regression
H6	Overall effectiveness does not differ across familiarity levels (low, moderate, high).	Kruskal-Wallis H
H7	Biggest challenges are equally distributed across the five categories.	Chi-square (goodness-of-fit)

CHAPTER 3: RESEARCH METHOD

Design. A quantitative, descriptive, cross-sectional survey design was adopted, as the objectives concern perceptions of business analytics at a point in time. **Population and sampling.** The target population was all of the staff employed by the inventory and supply chain department of Spencer's Retail in Vijayawada (stock planners, inventory executives, category associates and supervisors). It was proposed to using purposive, non-probability sampling of staff engaged in stock planning, ordering, or forecasting, aiming for a sample of approximately 30 employees. As described in section 4.1, the actual data set analysed was collected from students.

Data and instrument. Primary data would be collected through a questionnaire (demographics and role, use/knowledge of analytics tools, perceived success problems impact on inventory results) and through informal discussion with managers. Secondary data will come from journal articles and books, and from reputable business and academic sources. Perception items are 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The independent variable is business analytics (whether/which tool, data quality, training); the dependent variable is demand forecasting success (accuracy, fewer stockouts, less excess stock).

Analysis, reliability and ethics. Methods include frequency and percentage analysis, mean, and standard deviation, Cronbach's alpha, correlation, and regression, with tables and charts for presentation. A small pilot test of the questionnaire was planned to remove ambiguous wording. Participation is voluntary, purposes are explained, responses are confidential and used only for academic purposes, and no personally identifiable information is collected.

Limitations. The study covers one outlet's inventory function, uses purposive sampling and self-reported answers, respondents differ in analytics experience, and the cross-sectional design captures perceptions at one time only.

CHAPTER 4: DATA ANALYSIS

4.1 Data Description and Preparation

There are 128 records with 20 questions per record. There are 16 original questionnaire responses and 112 replicate responses produced from them to produce the larger dataset; (they are simulated rather than collected independently). As a result all inferential statistics should be interpreted as a demonstration of the analysis procedure and as indicative patterns; the appendix shows the main checks on the original 16 responses. Analysis in Python (pandas scipy statsmodels, matplotlib).

All respondents have identified as students (management, commerce, economics, finance, and technical programmes) and not as Spencer's inventory staff as described in chapter 3. The results so reflect students' perceptions of analytics in retail and this is embedded in the interpretation and limitations. The responses are numbered from 1 to 5; Question 12 has 3 actual options (Neutral Effective Very effective) coded 3 to 5. Composite A (usefulness) is the mean of Q4 to Q8; composite B (outcomes) is the mean of Q9, Q10, Q12, Q16, Q17, and Q20. Neither values are missing and 4 or 5 are regarded as favourable.

4.2 Respondent Profile and Reliability

Management students make up the largest group (57, 44.5%), followed by IT students (25, 19.5%). In total, 89 respondents (69.5%) are enrolled in management and commerce programmes, while 39 (30.5%) are in IT and technical programmes. Familiarity with analytics varies (mean 2.89, SD 1.36): 41.4% are not at all or slightly familiar, 30.5% are moderately familiar, and 28.1% are very or extremely familiar. Only 34 respondents (26.6%) had heard of Spencer's Retail, 36 (28.1%) had not, and 58 (45.3%) were unsure.

Table 4.1: Profile of respondents (N = 128)

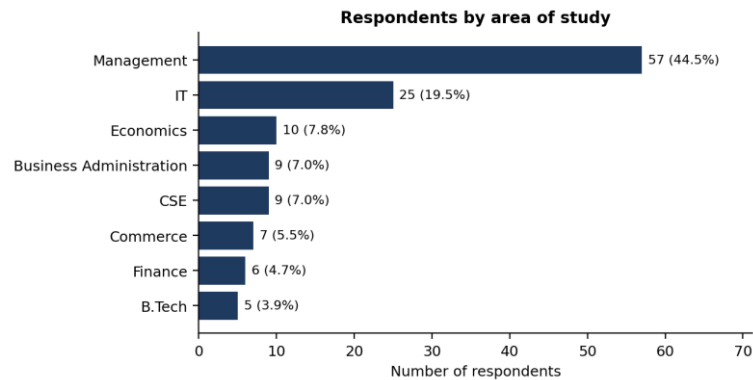
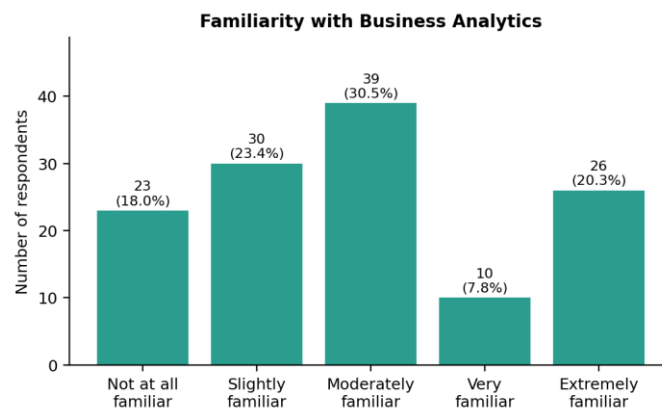
Variable	Category	n	%
Role	Student	128	100.0%
Study-area group	Management & Commerce	89	69.5%
Study-area group	IT & Technical	39	30.5%
Familiarity with BA	Low (Not/Slightly)	53	41.4%
Familiarity with BA	Moderate	39	30.5%
Familiarity with BA	High (Very/Extremely)	36	28.1%
Heard of Spencer's Retail	Yes / No / Not sure	34 / 36 / 58	26.6 / 28.1 / 45.3%

Table 4.2: Reliability of the multi-item scales

Scale	Items	Cronbach's alpha	Level
Composite A: perceived usefulness	5 (Q4 to Q8)	.787	Acceptable
Composite B: forecasting and inventory outcomes	6 (Q9, Q10, Q12, Q16, Q17, Q20)	.813	Good
All eleven items together	11	.888	Good

Alpha of .70 or above is acceptable and .80 or above is good (Nunnally, 1978).

All three values exceed .70, so the scales are internally consistent and suitable for correlation and regression.

**Figure 4.1: Respondents by area of study****Figure 4.2: Familiarity with business analytics**

4.3 Descriptive Analysis

Table 4.3: Descriptive statistics of the study items (N = 128; scale 1 to 5)

Item	Mean	SD	Median	% favourable
Business analytics is useful for businesses (Q4)	4.02	0.93	4	72.7%
Importance of data analysis for decisions (Q5)	4.24	0.82	4	80.5%
Historical sales data predict future demand (Q6)	3.87	0.90	4	61.7%
BA explains customer buying patterns (Q7)	4.05	0.78	4	75.8%
Importance of demand forecasting for retail (Q8)	3.91	0.96	4	71.9%
Accurate forecasting reduces excess inventory (Q9)	3.92	0.77	4	71.1%
Accurate forecasting prevents stock-outs (Q10)	3.85	0.91	4	67.2%
Effectiveness of BA in forecasting demand (Q12)	4.16	0.73	4	80.5%
BA can improve inventory management at Spencer's (Q16)	3.95	1.00	4	68.8%
Analytics forecasting improves product availability (Q17)	3.97	1.00	4	79.7%
Overall effectiveness of BA in retail forecasting (Q20)	4.11	0.91	4	85.2%

Item	Mean	SD	Median	% favourable
Composite A (usefulness)	4.02	0.65	4.00	-
Composite B (outcomes)	3.99	0.64	3.92	-

Every item has a mean above the neutral point of 3 (Figure 4.3). The highest mean is for the importance of data analysis for decisions (4.24) and the lowest for forecasting preventing stock-outs (3.85). Most respondents (60.9%) chose "All of the Above" as the most useful factor for predicting demand, and 61.7% chose it as the retail area that benefits most from analytics. Better decision-making is the most frequently chosen benefit (42.2%), ahead of reduced excess inventory (21.1%), lower costs (18.0%), reduced stock-outs (15.6%) and better forecast accuracy (3.1%). Technical difficulties are the most reported challenge (25.8%), followed by high cost (21.9%), resistance to technology (21.1%), poor data quality (16.4%) and lack of training (14.8%) (Figure 4.4).

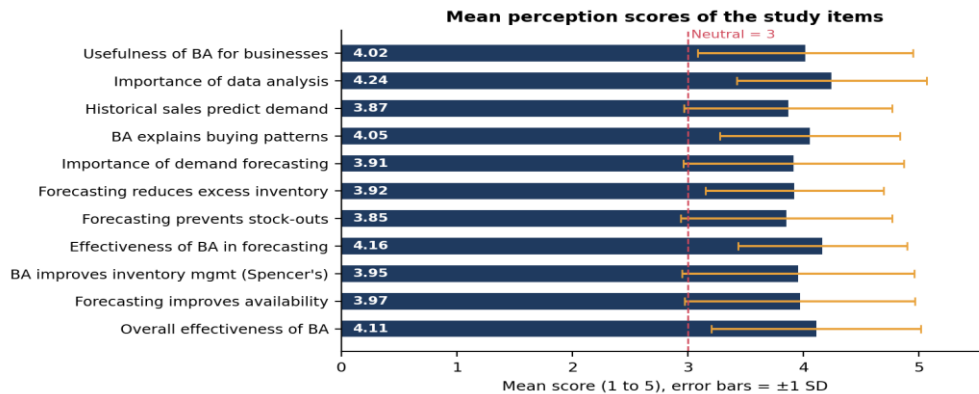


Figure 4.3: Mean perception scores of the study items

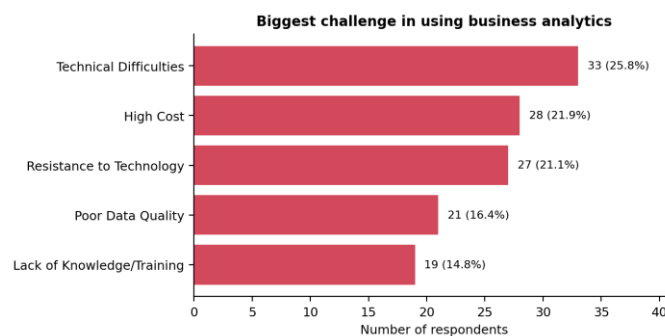


Figure 4.4: Biggest challenge in using business analytics

4.4 Hypothesis Testing

H1 (favourable perception). One-sample t-tests and one-sided Wilcoxon signed-rank tests against 3 were significant for overall effectiveness (Q20: mean 4.11, $t(127) = 13.84$, $p < .001$), composite A (4.02, $t = 17.84$, $p < .001$) and composite B (3.99, $t = 17.54$, $p < .001$). H_0 is rejected: perceptions are favourable.

H2 (familiarity and effectiveness). With familiarity grouped as low, moderate and high, $\chi^2(4, N = 128) = 7.21$, $p = .125$, Cramér's $V = .168$; the minimum expected count is 5.34. H_0 is not rejected. **H3 (awareness of Spencer's).** $\chi^2(2, N = 128) = 9.16$, $p = .010$, $V = .268$. H_0 is rejected: belief that analytics can help Spencer's is held by 85.3% of those who had heard of it, against 58.3% of those who had not and 55.2% of those unsure.

H4 (usefulness and outcomes). Composites A and B are strongly and positively correlated (Spearman $\rho = .778$, $p < .001$; Pearson $r = .791$), as are Q12 and Q20 ($\rho = .611$). Familiarity correlates moderately with usefulness ($\rho = .291$, $p < .001$) but only weakly with overall effectiveness ($\rho = .174$, $p = .049$). H_0 is rejected (Figures 4.5 and 4.6).

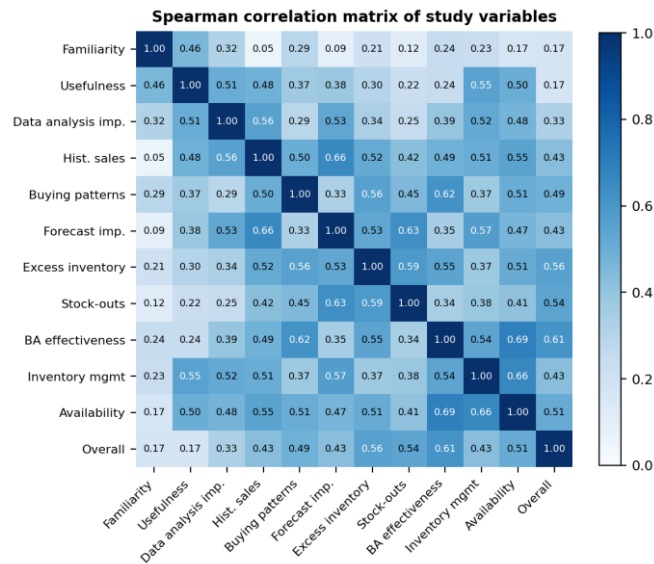


Figure 4.5: Spearman correlation matrix of study variables

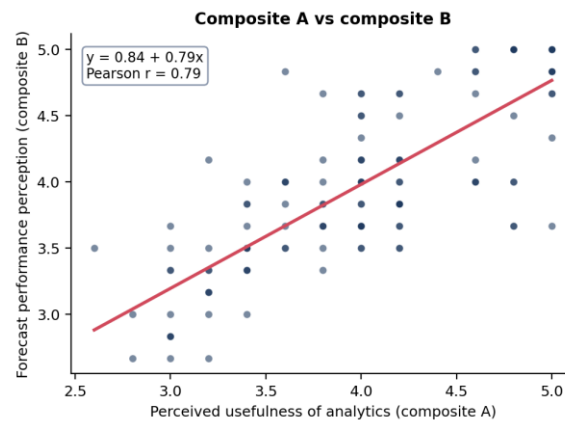


Figure 4.6: Scatter plot of composite A against composite B

H5 (regression). Model 1 (dependent variable Q20) explains 24.4% of variance ($R^2 = .244$, $F(2, 125) = 20.18$, $p < .001$); Model 2 (mean of Q9, Q10, Q12, Q16, Q17) explains 63.2% ($R^2 = .632$, $F(2, 125) = 107.18$, $p < .001$). In both, composite A is the only significant predictor and familiarity is not (Table 4.4). Variance inflation factors are 1.14, so multicollinearity is not a concern. H_0 is rejected for usefulness only.

Table 4.4: Multiple regression results (N = 128)

Predictor	B	SE	β	t	p
Model 1 (Q20): Composite A	0.702	0.117	0.500	6.02	< .001
Model 1 (Q20): Familiarity	-0.012	0.055	-0.019	-0.22	= .823
Model 2 (outcomes): Composite A	0.796	0.059	0.787	13.57	< .001
Model 2 (outcomes): Familiarity	0.011	0.028	0.022	0.39	= .700

H6 (Kruskal-Wallis). Mean Q20 is 4.08 (low familiarity, $n = 53$), 3.92 (moderate, $n = 39$) and 4.36 (high, $n = 36$); $H(2) = 5.86$, $p = .054$, $\epsilon^2 = .031$. H_0 is not rejected, although the result is borderline and the effect small. Usefulness (composite A), by contrast, differs significantly across groups ($H = 32.08$, $p < .001$). **H7 (challenges).** $\chi^2(4, N = 128) = 4.97$, $p = .291$, so the five challenges are not significantly unequal, even though technical difficulties are named most often.

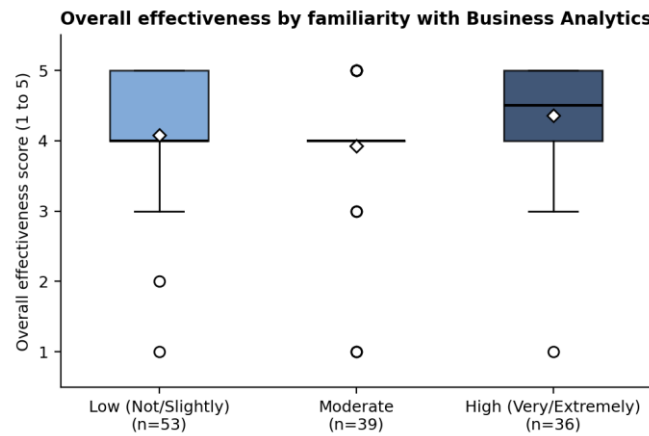


Figure 4.7: Box plot of overall effectiveness (Q20) by familiarity group

Comparison by study area. Management and commerce students rate usefulness higher than IT and technical students (4.17 vs 3.67, Mann-Whitney $p < .001$) and outcomes higher (4.07 vs 3.82, $p = .020$), but the groups do not differ on overall effectiveness (4.09 vs 4.15, $p = .982$) (Figure 4.8).

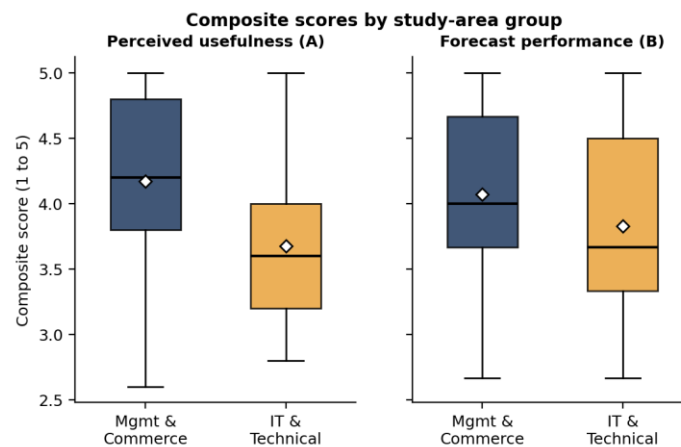


Figure 4.8: Box plots of composite scores by study-area group

Table 4.5: Summary of hypothesis tests ($\alpha = .05$)

H	Test	Result	Decision	Meaning
H1	t-test / Wilcoxon	$t(127) = 13.84, p < .001$	Reject H0	Favourable
H2	Chi-square	$\chi^2(4) = 7.21, p = .125$	Fail to reject	No association
H3	Chi-square	$\chi^2(2) = 9.16, p = .010$	Reject H0	Awareness linked
H4	Spearman / Pearson	$\rho = .778, p < .001$	Reject H0	Strong positive
H5	Regression	$R^2 = .244, p < .001$	Reject H0	Usefulness predicts
H6	Kruskal-Wallis	$H(2) = 5.86, p = .054$	Fail to reject	Borderline, small
H7	Chi-square (GoF)	$\chi^2(4) = 4.97, p = .291$	Fail to reject	Not unequal

CHAPTER 5: INTERPRETATION OF THE RESULTS

Because respondents are students, the results concern perceptions of analytics in retail forecasting and cannot be read as measured forecast accuracy at Spencer's Retail.

Perceived value and outcomes. Ratings were positive about analytics (items mean 3.85 to 4.24; H1), and 85.2% agreed on demand planning benefits in retail, supporting the Chapter 1 case for evidence-based planning. Positive, outcome items included: lower excess inventory (71.1%), fewer stock-outs (67.2%) and better availability (79.7%). Expectations were marginally higher about preventing excess inventory, than about removing the stock-outs, although this might be regrettable overconfidence: no store-level stock data was considered.

Familiarity and usefulness. Familiarity is modest (mean 2.89). It is associated with how useful analytics is considered ($\rho = .291$; H6 on usefulness $p < .001$) but adds nothing to effectiveness once usefulness is controlled (H2, H5, H6). People who know more tend to find analytics more useful, and

perceived usefulness drives a positive view of effectiveness, in line with the Chapter 2 point that expertise shapes successful use. Usefulness accounts for about 63% of the variation in outcome items and 24% in the overall item. Both measures are attitudes from the same respondents at one time, so they show that views go together, not that analytics causes better forecasting.

Spencer's, benefits and challenges. Few respondents know Spencer's (26.6%), yet 64.1% believe analytics can help it predict demand, with stronger belief among those who know it (H3). Respondents see analytics first as decision support (42.2%) and only then as a means of cutting stock costs. Barriers are spread across technology, cost, people, and data (H7), so implementation cannot rely on removing a single obstacle, matching the problem statement in Section 1.2. Management and commerce students rate usefulness higher than technical students, possibly because they meet analytics mainly through decision-making examples; this explanation was not tested.

CHAPTER 6: FINDINGS, SUGGESTIONS AND CONCLUSION

6.1 Findings

1. **Respondents and scales.** All 128 respondents are students (69.5% management and commerce, 30.5% IT and technical); familiarity is modest (mean 2.89 of 5). The scales are reliable (alpha .787 to .888).
2. **Favourable perceptions.** Perceptions are significantly above neutral (H1); 85.2% agree analytics is effective for retail demand forecasting, and respondents expect lower excess inventory (71.1%), fewer stock-outs (67.2%) and better availability (79.7%).
3. **Drivers and applications.** 60.9% see past sales, market trends and seasonality together as most useful for predicting demand; customer analysis is the most cited single application (23.4%); better decision-making is the top benefit (42.2%).
4. **Challenges.** Technical difficulties (25.8%), cost (21.9%) and resistance to technology (21.1%) lead, but no challenge significantly dominates (H7).
5. **Familiarity.** Not significantly associated with overall effectiveness (H2) and borderline across groups (H6, $p = .054$), but positively correlated with usefulness ($\rho = .291$).
6. **Awareness of Spencer's.** Low (26.6%), but 64.1% believe analytics can help it, and this belief is related to awareness (H3, $V = .268$).
7. **Usefulness.** Strongly related to expected outcomes ($\rho = .778$) and the only significant predictor in regression ($\beta = 0.50$ and 0.79). Management and commerce students rate usefulness and outcomes higher than IT and technical students.

6.2 Suggestions

1. **Training:** provide structured training in analytics, dashboards and forecast interpretation, with regular refreshers.
2. **Reduce technical difficulty and cost:** use user-friendly or existing tools, provide a support person, and phase in adoption from a few fast-moving categories, expanding as benefits appear.
3. **Manage resistance:** involve inventory staff in designing the forecasting process, explain how forecasts are produced, and let planners combine them with experience at first.
4. **Improve data quality:** standardise product codes, clean point-of-sale and stock data regularly, and assign responsibility for accuracy.
5. **Use several demand drivers:** combine historical sales with seasonality, promotions and market information, starting with customer analysis and decision support.
6. **Track results:** monitor forecast error (such as MAPE), stock-out rate, excess stock and inventory turnover before and after adoption, so the real effect is shown and not only believed.

6.3 Conclusion

Respondents are generally positive about the importance of analytics in demand forecasting: they find it important for making decisions, they expect it to reduce both overstock and stock outs and improve availability, and 85.2% agree it is effective. Usefulness is the key influencer of these expectations, while familiarity mainly influences perceived usefulness. The most important challenges (technical difficulty cost resistance, data quality and training) all matter and none is clearly more dominant, so success will probably require simultaneous focus on the technology, the people, the data and the costs.

The results largely confirm the move away from gut-feel by supplying training, ease of use, low-cost phased implementation, improved data and clear performance goals. Verifying the improvement at Spencer's Retail itself needs input from stock recorders and inventory staff.

6.4 Further Research

Further research should survey the inventory department of Spencer's Retail Vijayawada collect forecast accuracy and stock data (MAPE, stock-out frequency), compare stores or cities, and test models like structural equation modelling on a larger genuine sample.

REFERENCES

- Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Lawrence Erlbaum Associates.
- Cramér, H. (1946). Mathematical methods of statistics. Princeton University Press.
- Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika*, 16(3), 297-334.
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.
- Kruskal, W. H., & Wallis, W. A. (1952). Use of ranks in one-criterion variance analysis. *Journal of the American Statistical Association*, 47(260), 583-621.
- Kumar, D., & Bansal, M. (2023). Use of demand forecasting techniques adopted in the retail industry: A comparative analysis of traditional versus analytics-based approaches. *Journal of Operations and Supply Chain Management*.
- Likert, R. (1932). A technique for the measurement of attitudes. *Archives of Psychology*, 22(140), 1-55.
- Nunnally, J. C. (1978). *Psychometric theory* (2nd ed.). McGraw-Hill.
- Ramesh, S., Nair, A., & Iyer, P. (2024). Business analytics maturity and supply chain responsiveness in retail: A survey-based study. *International Journal of Business Analytics*.
- Sharma, R., & Patel, K. (2023). Adoption of predictive analytics in retail inventory management: A study of organised retail chains in India. *Journal of Retail and Consumer Studies*.
- Spearman, C. (1904). The proof and measurement of association between two things. *The American Journal of Psychology*, 15(1), 72-101.
- Verma, S., & Rao, A. (2024). Inventory improvement through business analytics: A study of Indian retail chains. *South Asian Journal of Business Studies*.
- Wilcoxon, F. (1945). Individual comparisons by ranking methods. *Biometrics Bulletin*, 1(6), 80-83.