

Marketing Analytics on EAZER's Product Performance

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ABSTRACT

This paper analyzes the business performance of EAZER, a retail company specializing in cleaning tools that emphasizes user convenience under the slogan “make your life easier.” The analysis focuses on evaluating the company’s product performance using key business analysis models. Specifically, the RFM (Recency, Frequency, Monetary) model is applied to identify the target product; regression analysis is used to assess sales trends; and correlation and sentiment analysis are conducted to investigate the causes of product returns and customer complaints. Findings reveal that among EAZER’s 13 products, Product 2 dominates in sales and demonstrates significant seasonal fluctuations. RFM analysis indicates a generally consistent customer engagement across products, while return and complaint patterns are concentrated at the product level and exhibit a negative correlation. These insights suggest a need for targeted strategies during low-demand seasons and a more responsive approach to managing negative customer feedback. Recommendations are developed using the 7Ps marketing mix and SMART objective frameworks. They include implementing dynamic promotional strategies during off-peak periods and establishing measurable, data-driven mechanisms to address negative sentiment and improve customer satisfaction. The analysis is based on 2023 data covering sales, returns, and customer complaints, and utilizes multiple statistical tools including t-tests and sentiment classification. Overall, the paper provides actionable insights to enhance EAZER’s performance and competitive standing in the B2C market.

KEYWORDS

Marketing Analytics; Product Performance Evaluation; RFM Model; Sentiment Analysis

1. INTRODUCTION

The global home cleaning tools market has experienced steady growth in recent years, driven by rising consumer expectations for efficiency, convenience, and product innovation. Increasing urbanization, busy lifestyles, and heightened awareness of hygiene—especially in the wake of the COVID-19 pandemic—have shifted consumer preferences toward functional, ergonomic, and durable cleaning solutions. Within this competitive landscape, companies must not only offer quality products but also leverage data-driven insights to sustain market relevance.

EAZER, a retail company specializing in cleaning tools under the slogan “make your life easier,” competes in this dynamic environment by providing a diverse product portfolio aimed at simplifying domestic cleaning tasks. However, maintaining competitiveness requires continuous monitoring of product performance and the agility to adapt marketing strategies in response to changing consumer behaviors, seasonal fluctuations, and evolving market conditions.

The purpose of this study is to evaluate EAZER’s product performance through a marketing analytics lens, integrating statistical modeling with strategic marketing frameworks. Specifically, the research

applies the RFM (Recency, Frequency, Monetary) model to identify high-value products, employs regression analysis to explore sales trends and seasonal effects, and uses correlation and sentiment analysis to investigate the drivers of product returns and customer complaints. The findings are then translated into actionable recommendations using the 7Ps marketing mix and SMART objectives frameworks.

This study makes two main contributions. First, it bridges quantitative analytics and qualitative marketing strategy by combining statistical techniques—such as t-tests, correlation coefficients, and sentiment classification—with practical business recommendations. Second, it addresses the often-overlooked relationship between negative customer sentiment and product life-cycle management, offering a targeted approach to improving both sales performance and brand perception. By focusing on 2023 sales, returns, and customer feedback data, the research provides EAZER with evidence-based insights to refine its pricing, promotion, and customer service strategies, ultimately enhancing its competitive standing in the B2C home cleaning tools sector.

2. METHODOLOGY

This study evaluates EAZER’s product performance using a quantitative, data-driven marketing analytics approach. The analysis is based on the company’s 2023 operational data, which includes monthly sales volumes, return rates, and customer complaint records for 13 cleaning tool products. The dataset covers both transactional metrics and qualitative feedback, enabling a multi-dimensional performance assessment.

Four analytical methods were employed. First, the RFM (Recency, Frequency, Monetary) model was adapted for product-level evaluation, replacing traditional customer metrics with average monthly sales, return rates, and negative complaint rates. This modification allowed for the classification of products into performance tiers. Second, regression analysis was applied to examine monthly sales patterns, particularly focusing on identifying seasonal fluctuations in the best-performing product. Third, Pearson’s correlation analysis and t-tests were conducted to test the statistical significance of relationships between sales and return rates. Finally, sentiment analysis, including keyword extraction and word cloud visualization, was performed on customer complaint data to identify common quality issues and sources of dissatisfaction.

This methodological design integrates statistical rigor with practical marketing tools, ensuring that results are both reliable and actionable. The combination of quantitative modeling and qualitative insights provides a robust foundation for formulating targeted marketing strategies and operational improvements.

3. PERFORMANCE EVALUATION AND ANALYTICAL FINDINGS

3.1. Product Hierarchical Rating Using the RFM Model Concept

The RFM model, an analytical tool for evaluating customer value, concentrates on three key indicators: Recency, Frequency and Monetary, which is widely applied in marketing and customer relationship management. (Winston, 2014). Similarly, the core concept of this model can be extended to assess EAZER’s products performance by modifying these indicators to another 3 metrics: average monthly total sales, return rates, and negative complaint rates. As depicted in Table 1, the 13 products were rated from 1 to 5 according to their performance across these three dimensions (see detail calculation in Appendix 1).

Subsequently, the overall performance charts (Figure 1) are generated.

Table 1. Table for Specific Rating of 13 products

Product Type	Final score	Performance
Product 2	4.0	excellent
Product 6	4.0	excellent
Product 10	3.7	good
Product 8	3.6	good
Product 13	3.1	fine
Product 5	2.9	fine
Product 1	2.6	average
Product 12	2.3	average
Product 7	2.3	average
Product 9	2.3	average
Product 11	1.9	poor
Product 3	1.8	poor
Product 4	1.5	poor

Notes: 13 products are sorted in descending order of final score (refer to Appendix 1 for the calculation)

Product classification using RFM theory

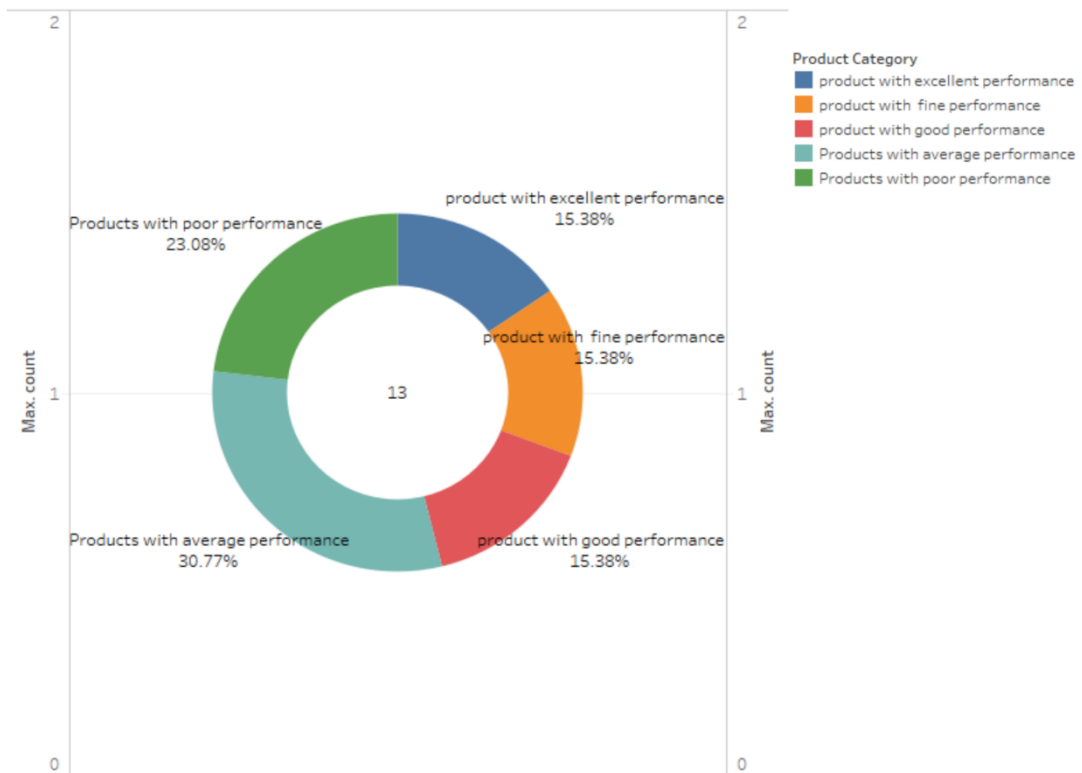


Figure 1. EAZER’s 13 Products Classification of EAZER with RFM Model

Notes: rate the product from the three dimensions (1-5) and calculate the final score based on the given ratio and make the classification according to the final score.

2023 EAZER Annual Sales Proportion of 13 Products

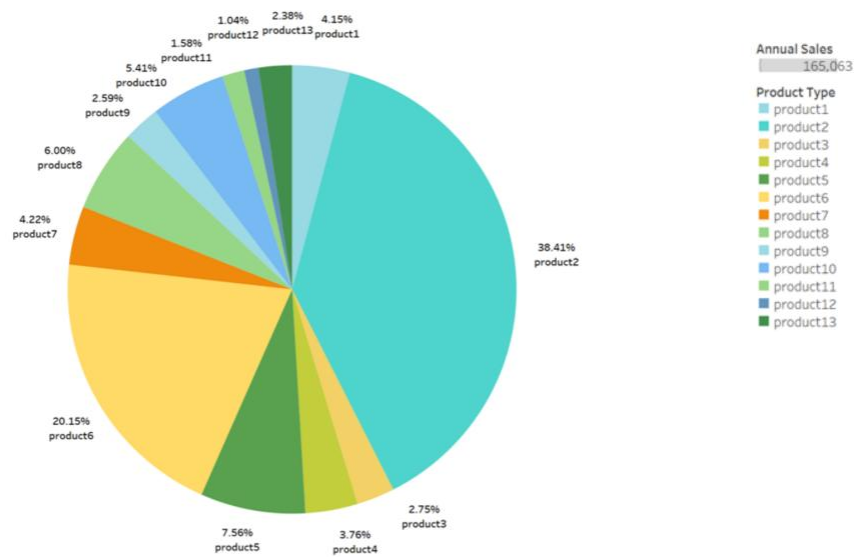


Figure 2. Pie Chart of 2023 EAZER’s 13 Products Annual Sales Distribution

Notes: Annual sales of each product are the sum of its total sales of each month in 2023.

Overall, the distribution of products with different performances is relatively dispersed (Figure 1). The proportion of products with ‘average performance’ is the highest, reaching 30.77%, indicating that there are more products with moderate performance in this product group. The rest categories are numerically close. This indicates that the performance of this product group exhibits a distinct hierarchical structure. Specifically, no single performance level overwhelmingly dominates the entire group. This distribution means that the overall performance of the product group is relatively diverse, with both outstanding and underperforming products.

Concentrating on the extreme values (in conjunction with Table 1 and Figure 2, 3), it is evident that Product 2 demonstrates exceptional performance. In terms of sales proportion, it accounts for 38.41%, which surpasses one third of the total sales of this product group, thereby occupying a dominant position. Additionally, in performance rating, it is categorized as an ‘excellent product’ (4.0). This means that Product 2 is highly favored by EAZER’s target audience. Therefore, this article will center its analysis on Product 2.

3.2. Seasonal Fluctuations: Monthly Sales Insight

3.2.1. Data-driven Exploration of Sale Trend of Product 2

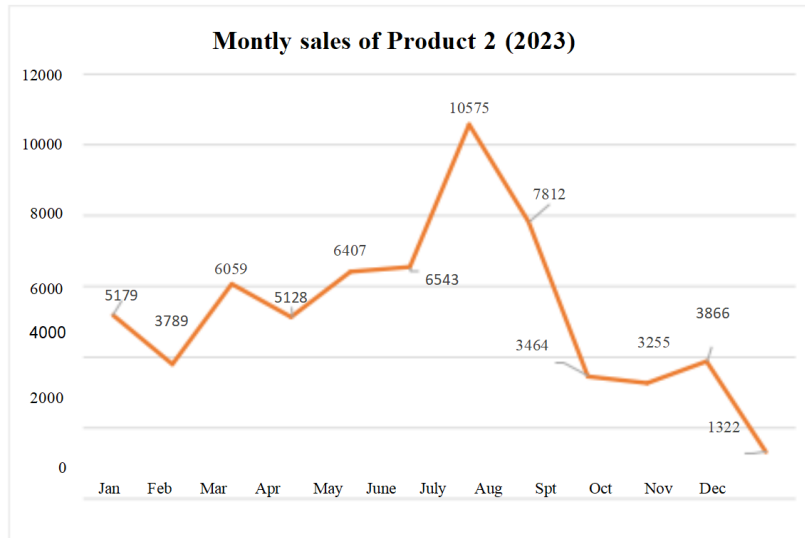


Figure 3. Line Chart of Monthly Sales of Product 2 (2023)

Notes: The vertical axis denotes the sales volume for each period.

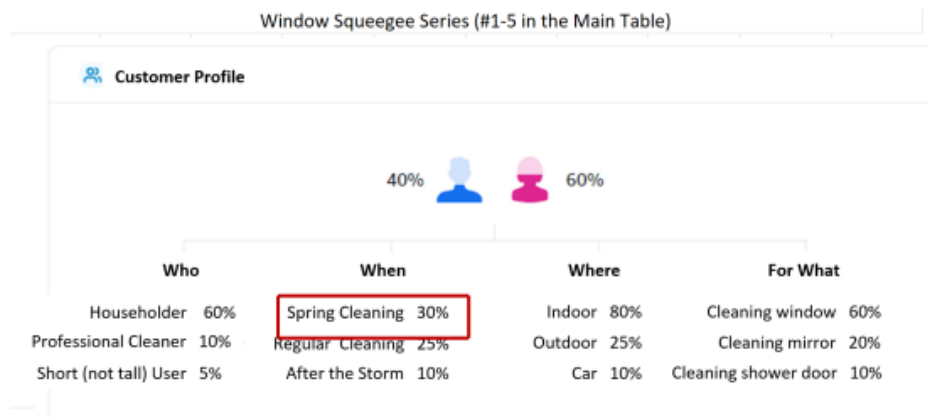


Figure 4. Customer Profile

Notes: Product 2 is belonging to the product group ‘Window Squeegee Series’ (see detail Product name and product type classification in Appendix 1)

The line chart (Figure 3) reveals a pattern of initial fluctuating growth, followed by a peak in July (10575), and finally a notable decline. This trend suggests a progressive increase in the demand for Product 2 during the first half of the year. As illustrated in Figure 4, the increasing customer demand for spring cleaning (30%), a seasonal factor, has contributed to the creation of a conducive market environment. This seasonal factor has been instrumental in enabling mid-year sales to constitute the dominant portion of Product 2's annual sales volume.

The susceptibility of products to seasonal factors, resulting in significant sales fluctuations, poses potential hazards. Firstly, it impedes enterprises from accurately planning production scales and rhythms. For instance, prior to peak seasons, enterprises need to increase production and stock up in advance. However, due to large-scale demand fluctuations, inaccurate forecasts may lead to insufficient production, thereby missing out on sales opportunities. Alternatively, over-production may occur, causing inventory backlogs and resulting in cost waste.

Secondly, such substantial fluctuations render it difficult to maintain consistent marketing strategies. Enterprises struggle to sustain stable market promotion and brand-building strategies. Investing marketing resources during off - peak seasons may yield sub-optimal results due to low demand, leading to cost inefficiencies. During peak seasons, although demand is high, hasty marketing efforts may lack depth and targeting.

Moreover, during off-peak seasons, customer activity is low, reducing interactions between enterprises and customers, which may lead to a weakened relationship. During peak seasons, when business is bustling, inconsistent service quality may degrade the customer experience and lower satisfaction levels, thereby affecting long - term customer relationships.

3.2.2. Confirmation: Regression Analysis

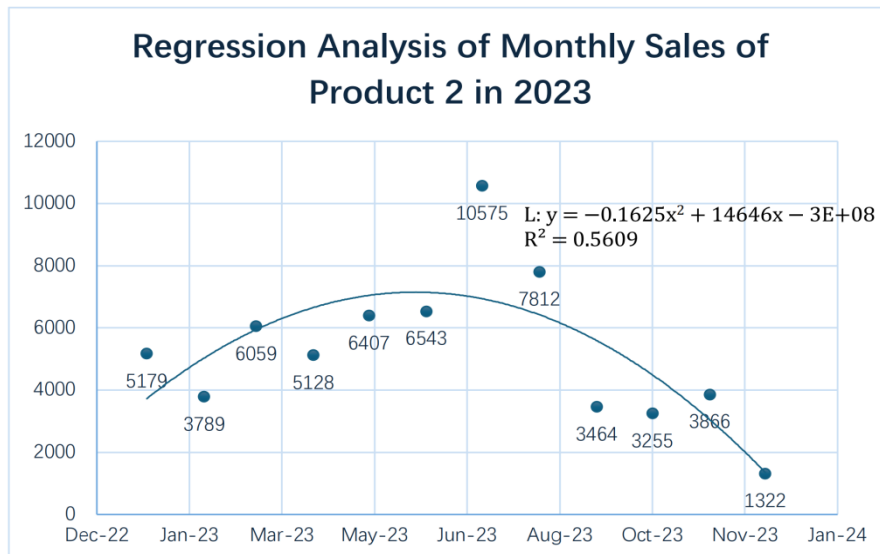


Figure 5. Regression Analysis of Monthly Sales of Product 2 in 2023

Notes: The curve equation: $L: y = -0.1625x^2 + 14646x - 3E+08$; $R^2 = 0.5609$; Goodness of fit: $R^2 = 0.5609$

The quadratic coefficient of $L: y = -0.1625x^2 + 14646x - 3E+08$ is negative (- 0.1625), indicating that there is a ‘ceiling’ in sales growth, which gradually decreases after reaching its peak. The overall regression curve conforms to the seasonal fluctuation trend mentioned in 3.2.1.

However, the Goodness of fit $R^2 = 0.5609$ indicates that the quadratic regression model explains about 56% of the sales fluctuations, and the fitting effect is moderate. The remaining 44% that cannot be explained may be influenced by external factors (promotions, competitors and unexpected events) and need to be supplemented with other analytical methods for explanation. Meanwhile, the extremely high first-order coefficient (14646) indicates significant sales growth in the short term while is unsustainable in the long term. Thus, caution should be exercised against excessive reliance on short-term strategies.

3.3. Returns & Negative Complaint Analysis

3.3.1. Negative Correlation between Sales and Return Rates

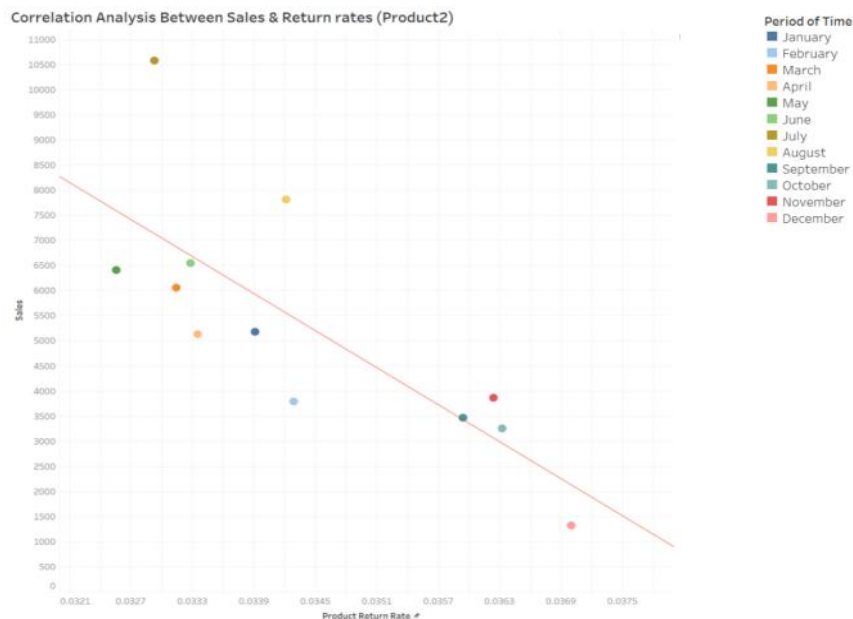


Figure 6. Scatter Plot of the Correlation between Return Rates and Sales

Notes: The horizontal axis represents the monthly return rate, and the vertical axis represents the monthly sales revenue.

Range of Coefficient	Description of Strength
±.81 to ±1.00	Very Strong
±.61 to ±.80	Strong
±.41 to ±.60	Moderate
±.21 to ±.40	Weak
±.00 to ±.20	Weak to no relationship

Figure 7. Relationship between the range of coefficient r and correlation strength

Notes: Available at Lecture Slides 6: Transactional Analytics (II)

Figure 6 depicts a negative correlation between the sales revenue and return rate of Product 2 ($r = -0.776$, see detailed calculation in Appendix 2), meaning that the higher the sales revenue, the lower the return rate. To verify the significance of the correlation, we conducted a t-test on r.

(1) T-test analysis

Correlation coefficient: $r = -0.776$ (Pearson's r)

Sample size: $n = 12$ (12 months of data)

Degrees of freedom: $df = n - 2 = 10$

The t-value converts the r-value into a t-distributed statistic:

$$t = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}} = \frac{-0.776\sqrt{10}}{\sqrt{1-(-0.776)^2}}$$

$$t = \frac{-2.454}{0.631} \approx -3.89$$

Final t-value:

$t = -2.454 / 0.631 \approx -3.89$ Absolute value: $|t| = 3.89$


(2) Determine the p-value

Two-tailed test: Tests whether r is significantly different from 0 (regardless of direction). Using a t-table, (df=10, t=3.89) corresponds to a two-tailed p-value between 0.001 and 0.005.

Excel formula = T.DIST. 2T(3.89, 10) → Returns $p \approx 0.003$ (see detail deduction in Appendix 2).

Table of the Student's t-distribution

The table gives the values of $t_{\alpha, \nu}$ where $\Pr(T_\nu > t_{\alpha, \nu}) = \alpha$, with ν degrees of freedom



α	0.1	0.05	0.025	0.01	0.005	0.001	0.0005
1	3.078	6.314	12.076	31.821	63.657	318.310	636.620
2	1.886	2.920	4.303	6.965	9.925	22.326	31.598
3	1.638	2.353	3.182	4.541	5.841	10.213	12.924
4	1.533	2.132	2.776	3.747	4.604	7.173	8.610
5	1.476	2.015	2.571	3.365	4.032	5.893	6.869
6	1.440	1.943	2.447	3.143	3.707	5.208	5.959
7	1.415	1.895	2.365	2.998	3.499	4.785	5.408
8	1.397	1.860	2.306	2.896	3.355	4.501	5.041
9	1.383	1.833	2.262	2.821	3.250	4.297	4.781
10	1.372	1.812	2.228	2.764	3.169	4.144	4.587
11	1.363	1.796	2.201	2.718	3.106	4.025	4.437
12	1.356	1.782	2.179	2.681	3.055	3.930	4.318
13	1.350	1.771	2.160	2.650	3.012	3.852	4.221
14	1.345	1.761	2.145	2.624	2.977	3.787	4.140
15	1.341	1.753	2.131	2.602	2.947	3.733	4.073
16	1.337	1.746	2.120	2.583	2.921	3.686	4.015
17	1.333	1.740	2.110	2.567	2.898	3.646	3.965
18	1.330	1.734	2.101	2.552	2.878	3.610	3.922
19	1.328	1.729	2.093	2.539	2.861	3.579	3.883
20	1.325	1.725	2.086	2.528	2.845	3.552	3.850
21	1.323	1.721	2.080	2.518	2.831	3.527	3.819
22	1.321	1.717	2.074	2.508	2.819	3.505	3.792
23	1.319	1.714	2.069	2.500	2.807	3.485	3.767
24	1.318	1.711	2.064	2.492	2.797	3.467	3.745
25	1.316	1.708	2.060	2.485	2.787	3.450	3.725
26	1.315	1.706	2.056	2.479	2.779	3.435	3.707
27	1.314	1.703	2.052	2.473	2.771	3.421	3.690
28	1.313	1.701	2.048	2.467	2.763	3.408	3.674
29	1.311	1.699	2.045	2.462	2.756	3.396	3.659
30	1.310	1.697	2.042	2.457	2.750	3.385	3.646
40	1.303	1.684	2.021	2.423	2.704	3.307	3.551
60	1.296	1.671	2.000	2.390	2.660	3.232	3.460
120	1.289	1.658	1.980	2.358	2.617	3.160	3.373
∞	1.282	1.645	1.960	2.326	2.576	3.090	3.291

Figure 8. The p-value table to obtain the p-value from the t-score

Notes: (Sapkota, 2024) Available at: <https://microbenotes.com/p-value/>

(3) Significance judgment

$p \approx 0.003 < 0.01$ means highly significant at the 99% confidence level, rejecting the null hypothesis ($r=0$). In conclusion, the negative correlation between sales and return rate is statistically significant.

This finding runs counter to the traditional notion that sales growth is typically associated with a concurrent rise in return rates. It offers important insights into consumer behavior and market dynamics. For instance, the peak sales volume recorded in July, accompanied by the lowest return rate of 3.29%, strongly suggests that the product effectively satisfied market demands during this period. This outcome can be attributed to the product's alignment with consumer expectations, leading to a reduced likelihood of post-purchase returns.

In contrast, during the off-peak season, as exemplified by December, which witnessed the lowest sales and the highest return rate (3.70%). One primary root lies in the weakened demand and the absence of prominent consumption stimulations during this period. With a lack of clear purchasing objectives, consumers tend to engage in random browsing and impulsive buying. These purchases

are often made on a tentative or exploratory basis, increasing the probability that the products acquired may not fully meet their needs.

Consequently, consumers are more inclined to initiate returns due to product-related dissatisfaction or mismatch with their requirements.

3.3.2. Return Reason Analysis

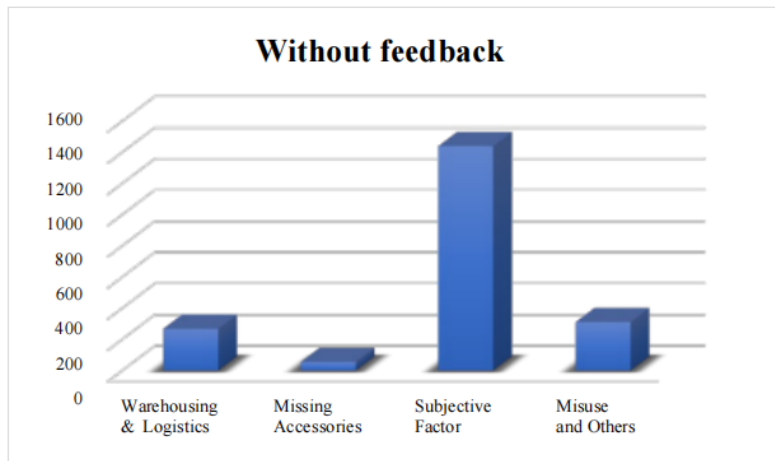


Figure 9. Product return without feedback

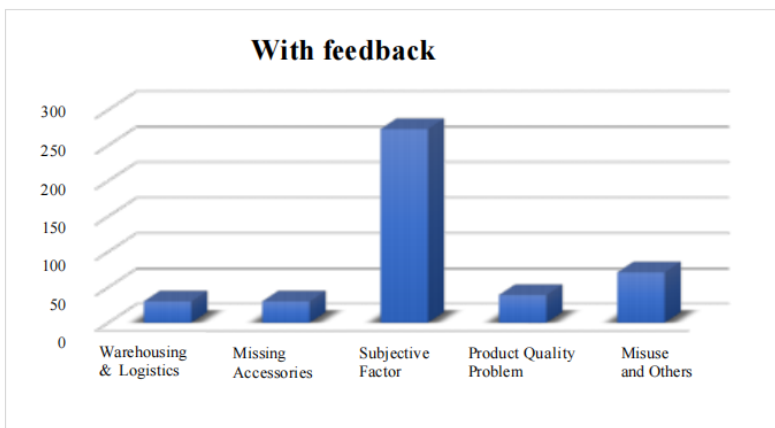


Figure 10. Product return with feedback

To figure out the underlying causes of product returns, a comprehensive analysis of the return rationales was conducted. Figures 9 and 10 conclude that regardless of feedback, customers' subjective emotions are the main reason for returns. Additionally, a specific category has been added ('Product Quality Issues'), indicating that feedback mechanisms can expose hidden pain point: quality defects.

4.1.1. Price - Dynamic pricing

Dynamic pricing is a strategy that adjusts product prices in real-time based on market demand, competitive conditions, and costs (Lange & Schlosser, 2025). Price strategy adjustments can directly influence consumers' purchasing decisions (Figure 13).

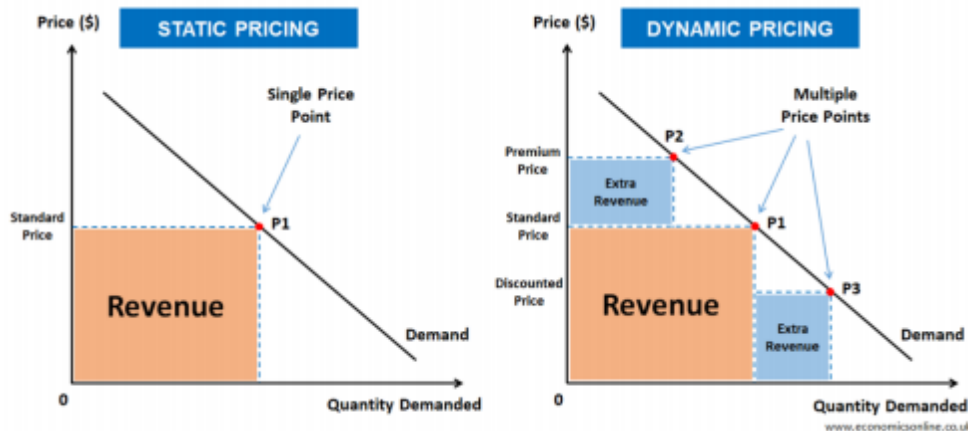


Figure13. Dynamic Pricing

Notes: (Ansari, 2024). Available at: <https://www.economicsonline.co.uk/definitions/dynamic-pricing- explained.html/>

Dynamic pricing strategies can be tailored to seasonal fluctuations for EAZER. During peak demand periods, EAZER can appropriately increase prices to maximize profits, while in off seasons, it can adopt price-reduction strategies to attract price sensitive consumers. For example, in December, the non-rainy winter period, the demand for window squeegees plummeted. A 20% - 30% price reduction may incentivize consumers who initially had no purchase intention to make a purchase due to the improved price-value proposition. This strategy effectively converts potential customers into actual buyers, thereby boosting product sales volume.

Regarding loyal customers, time-bound discount can be introduced during off seasons. As argued by Bliss (2018), such time-limited offers create a sense of urgency among consumers, compelling them to make immediate purchasing decisions. Even when there is no immediate need for the product, customers may choose to stock up due to the attractive price.

Dynamic pricing enables EAZER to predict consumer responses to varying price levels and demand changes with greater accuracy by leveraging market feedback and sales data.

Through the analysis of sales data following price adjustments, the company can gain insights into consumer price sensitivity and demand elasticity (Ansari, 2024). These insights facilitate more informed adjustments to production planning and inventory management strategies, thereby minimizing the risks of overproduction or stockouts.



Figure 14. Flow Chart for the Concept of EAZER Dynamic Pricing

4.1.2. Promotion-Social Media Marketing & Influencer Economy

Social Media Marketing plays a pivotal role in off-season marketing strategies. It enables enterprises to maintain brand visibility, uncover latent consumer demands, and proactively lay the groundwork for the peak sales season (Tuten & Solomon, 2018). For example, EAZER can launch a ‘Window Cleaning Campaign’ across multiple platforms (Instagram, Facebook, Tik-Tok etc.). Participants are required to purchase EAZER window squeegees, document their window-cleaning process through video content, and upload these videos to the designated platforms along with positive complaints. In return, they will be eligible for predefined incentives, which can range from monetary rewards and product discounts.



Figure 15. Social Media Marketing

Notes: (Maria Muntean, 2022). Available at: <https://www.springboard.com/blog/business-and-marketing/get-into-social-media-marketing/>

To maximize the campaign's reach and impact, EAZER should strategically engage influencers. The selection process should prioritize influencers specializing in home cleaning and lifestyle product complaints, as their follower demographics closely align with EAZER's target customer base. These

influencers will serve as brand advocates, creating high-quality demonstration videos that showcase the effectiveness of EAZER window squeegees. By leveraging their established credibility and large followings, influencers can effectively encourage their audience to participate in the challenge. Their endorsement not only introduces the product to a wider audience but also builds trust, as consumers often rely on influencer recommendations when making purchasing decisions.

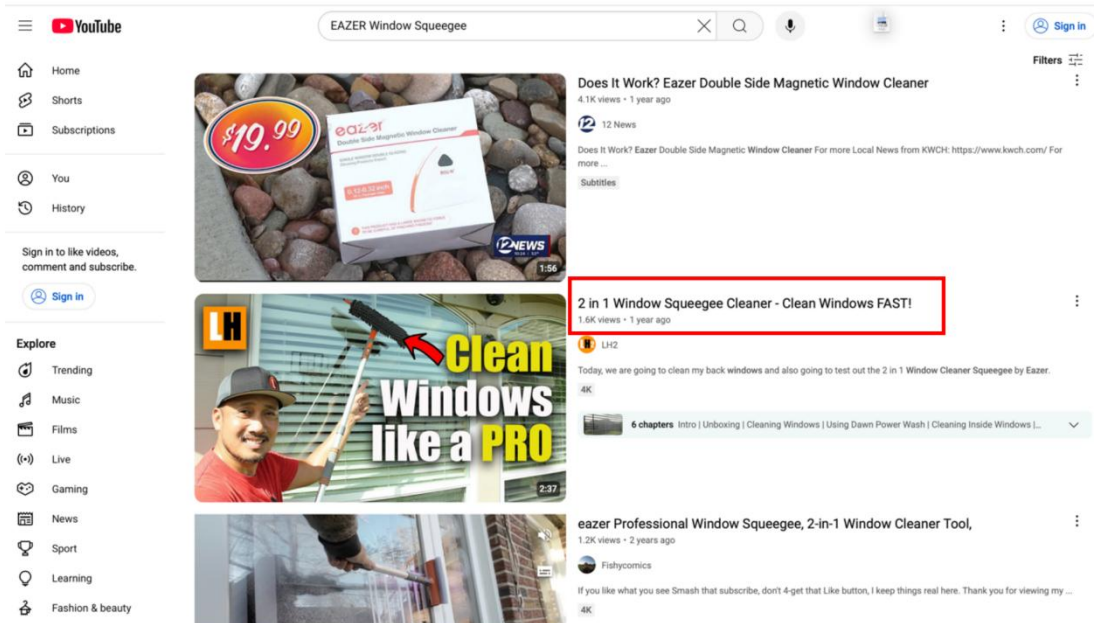


Figure 16. Influencer Video with EAZER’s Window Squeegee

Notes: Available on YouTube at: <https://www.youtube.com/watch?v=ugcnoD5iOT4>

This integrated approach to social media management and influencer collaboration represents a data-driven strategy (Belanche, Casaló, Flavián & Ibáñez-Sánchez, 2021). By tracking key performance indicators such as engagement rates, video views, and conversion metrics, EAZER can assess the campaign's success and refine future marketing efforts. Through continuous optimization, the brand can establish a strong social media presence, foster customer loyalty, and ultimately achieve sustainable growth in the competitive consumer market.

4.2. Negative Complaint Management: SMART Model

In a competitive market environment, negative complaint management is of paramount importance for enhancing customer satisfaction and optimizing products and services. The SMART model, a widely recognized framework for goal setting and evaluation, encompasses five key criteria: Specificity, Measurability, Achievability, Relevance, and Time-bound (Neiger & Thackeray, 2002). EAZER can set measurable goals based on SMART model.



Figure 17. SMART Model

Notes: (Tunde Phillips, 2022). Available at: <https://printivo.com/blog/smart-goals/>

Table 3. Summary of SMART Model & EAZER Negative complaints management

SMART Model & EAZER Negative complaints management		
Specific	Identify cause of negative complaints	Natural Language Processing (NLP)
	Establish a classification and management system	a negative complaint classification matrix
Measurable	Setting Quantitative Indicators	Negative Complaint Rate (NCR)
		Key Problem Improvement Rat (KPIR)
		Customer satisfaction rebound index (CSRI)
	Visualization	Dashboard construction(BI) study generation
Attainable	Quickly respond to negative reviews	Chat bot & Customer Service Team
		CRM Model tracking
	Resource matching	Building cross-departmental teams
Relevant	All goals and measures revolve around improving customer satisfaction, loyalty, and promoting business growth.	
Time-bound	short-term	Complete the sorting and classification of backlogged negative complaints and develop preliminary plans.
	mid-term	Implement improvement measures for high-frequency issues and monitor their effectiveness.
	Long term	Continuously tracking the complaint rate, consolidating achievements, and forming a long- term mechanism.

The table has summarized the approach to negative-complaint management for EAZER according to SMART Model. Natural Language Processing (NLP) is utilized to discern the root causes of negative complaints, and a classification and management matrix is put in place to identify core issues, thereby ensuring that the management endeavors are well-focused and unambiguous. To measure the

effectiveness of this management, quantitative metrics like the Negative Complaint Rate (NCR), Key Problem Improvement Rate (KPIR), and Customer Satisfaction Rebound Index (CSRI) are established (Birchmier, 2024). Business Intelligence (BI) tools are then used to create dashboards and generate studies, enabling data visualization for a precise assessment of outcomes.

For operational feasibility, chatbots and customer service teams are mobilized to promptly address negative reviews. Simultaneously, cross-departmental teams are assembled to optimize resource allocation, ensuring that initiatives in negative-complaint management can be effectively executed with the support of appropriate human and technological resources.

All objectives and strategies are centered around enhancing customer satisfaction and loyalty while driving business growth, thus aligning negative-complaint management closely with the company's core goals. The process is structured into three distinct phases: in the short term, backlogged negative complaints are sorted, categorized, and initial solutions are developed; in the medium term, improvement measures for recurrent issues are implemented and their efficacy is monitored; in the long term, the complaint rate is continuously tracked, achievements are solidified, and a sustainable mechanism is established.

This approach presents a highly systematic framework for negative complaint management. By integrating aspects such as cause identification, quantitative assessment, resource allocation, goal alignment, and time-phased planning, it offers a holistic perspective. The emphasis on core objectives like boosting customer satisfaction, along with the utilization of quantitative indicators and data visualization, provides a solid foundation for management effectiveness and making informed decisions. However, there are fields that warrant refinement. For example, while cross-departmental teams are formed, the lack of clear assignment and defined duty boundaries may lead to potential responsibility-shirking.

Additionally, the quantitative indicators, which are currently somewhat isolated, could benefit from an exploration of their inter-connections. For instance, understanding the relationship between NCR and CSRI more deeply could significantly enrich the comprehension of negative-complaint management.

5. CONCLUSION

This study evaluated EAZER's product performance in the competitive home cleaning tools market using an integrated marketing analytics approach. Through the RFM model, regression analysis, and correlation and sentiment analysis, Product 2 was identified as the top performer, showing strong sales but notable seasonal fluctuations. A significant negative correlation between sales and return rates indicated that peak demand periods align with higher customer satisfaction, while off-peak seasons tend to see more returns and negative feedback.

Product quality—particularly material durability and usability—emerged as a primary source of customer dissatisfaction. Based on these insights, targeted strategies were proposed, including dynamic pricing to smooth seasonal demand, social media and influencer campaigns to enhance brand engagement, and a SMART-based complaint management system to address recurring issues.

The research demonstrates how quantitative analysis can be paired with strategic marketing frameworks to generate actionable insights for improving performance and competitiveness. While the findings provide a practical roadmap for EAZER, the study's scope is limited to one year of data and a single product category. Future work should extend the time frame, include more product lines, and explore predictive models to better anticipate market shifts and inform long-term strategic planning.

REFERENCES

- [1] Ansari, S. (2024) Dynamic Pricing Explained. Available at: <https://www.economicsonline.co.uk/definitions/dynamic-pricing-explained.html/> [Accessed on April 21, 2025].
- [2] Belanch, D., Casaló, L. V., Flavián, M. and Ibáñez-Sánchez, S. (2021) Understanding influencer marketing: The role of congruence between influencers, products and consumers, *Journal of business research*, 132, pp. 186–195.
- [3] Birchmier, D. (2024) 21 customer service KPIs every support team needs to track. Available at: <https://www.zendesk.com/blog/customer-support-kpis-need-track/> [Accessed on April 24, 2025].
- [4] Bliss, M. (2018) Here's How to Get Customers During Your Off-Season. Available at: <https://www.simplybusiness.com/resource/getting-customers-during-the-off-season/> [Accessed on April 24, 2025].
- [5] College Vidya Team (2024) What are the 7Ps of Marketing? Available at: <https://collegevidya.com/blog/7-ps-of-marketing-explained/> [Accessed on April 21, 2025].
- [6] Lange, F. and Schlosser, R. (2025) Dynamic pricing with waiting and price-anticipating customers. *Operations Research Perspectives*, (14)100337, Available at: <https://doi.org/10.1016/j.orp.2025.100337> [Accessed on April 23, 2025].
- [7] Muntean, M. (2022) How to Get into Social Media Marketing. Available at: <https://www.springboard.com/blog/business-and-marketing/get-into-social-media-marketing/> [Accessed on April 22, 2025].
- [8] Neiger, B. L. and Thackeray, R. (2002). Application of the SMART Model in two successful social marketing projects. *American Journal of Health Education*, 33 (5), 301 - 303.
- [9] Phillips, T. (2022) Smart Goals. Available at: <https://printivo.com/blog/smart-goals/> [Accessed on April 21, 2025].
- [10] Sapkota, A. (2024) P Value: Definition, Formula, Table, Calculator, Significance. Available at: <https://microbenotes.com/p-value/> [Accessed on April 24, 2025].
- [11] Tuten, T.L. and Solomon, M.R. (2018) *Social media marketing*. Los Angeles: SAGE.
- [12] Winston, W. L. (2014) *Marketing Analytics : Data-Driven Techniques with Microsoft Excel*,
- [13] John Wiley & Sons, Incorporated, Newark. Available at: <https://ebookcentral.proquest.com/lib/nottingham/detail.action?docID=1629159>. [Accessed on April 21, 2025].