NEW YORK UNIVERSITY

Behavioral Forecasting of Sunscreen Sales Using Reviews and Competitor Analysis

Final Project Report

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1. Business Understanding

In the skincare retail market, understanding and predicting product sales is critical for inventory planning, marketing strategy, and competitive positioning. Traditional sales forecasts often rely on historical sales trends and seasonal patterns, but they may not capture real-time shifts in consumer sentiment or competitive pressures. Our goal in this project is to enhance sales forecasting for Neutrogena's sunscreen products by incorporating behavioral data from customer reviews and competitor analysis. We focus on three Neutrogena products and two key competitor products in the facial sunscreen category. By analyzing what customers are saying (review sentiment, topics of discussion, complaints) and how competitor products are performing in the eyes of consumers, we aim to create a more responsive and accurate forecast of future sales.

1.1 Why this matters:

Online reviews have a known impact on consumer purchasing behavior. In fact, around 95% of shoppers read reviews before buying, and studies have found that even a one-star increase in average rating can translate to a 5–9% rise in revenue(wisernotify). Conversely, negative feedback can quickly dampen sales. Harnessing this information in forecasting gives us a forward-looking indicator of demand; if people's opinions (as reflected in reviews) improve or worsen, sales may follow suit. Additionally, competitive analysis is key to finding a market advantage

(sba). Knowing how rival products are perceived and how they sell provides context for our own performance. For example, if a competitor's sunscreen is suddenly praised for a new formula, it might attract customers away from Neutrogena, impacting our sales. By monitoring such trends, our forecast can adjust expectations proactively.

1.2 Business Objective:

We framed our problem as predicting weekly unit sales for each product, 4–8 weeks in advance, using not just past sales data but also signals from consumer reviews and competitor metrics. Success is defined by improved forecast accuracy (e.g., lower error rates like RMSE) compared to a baseline model that doesn't use review data. Improved accuracy directly leads to better stock management (reducing stockouts or overstock costs) and more targeted marketing – ultimately increasing revenue and customer satisfaction. For instance, anticipating a sales dip in advance might prompt a promotional campaign to counteract it, whereas anticipating a surge ensures inventory meets demand. We also aim to identify why sales may change – for example, if a rise in negative reviews about "greasiness" is forecasted to reduce sales, the business can intervene by addressing that product issue or adjusting messaging.

1.3 Scope and Constraints:

Our analysis focuses on three specific Neutrogena facial sunscreens (call them Product A, Product B, and Product C for confidentiality) and two competitor products (one from EltaMD, one from L'Oréal). We have historical review data from 2018–2025 and price-related data for 2024–2025. One constraint is that actual sales data for the full period is limited; hence we construct a proxy for sales using reviews (details in Data Understanding). We assume the relationship between review metrics and sales holds relatively steady (e.g., a positive review today has a similar effect on sales as a positive review last year). Another assumption is a 2% review rate, meaning roughly 1 in 50 buyers leaves a review – a figure in line with e-commerce statistics (only about 1–2% of Amazon buyers leave reviews(wisernotify). Using this, we later convert our predicted "proxy sales" into estimated actual unit sales. We also must consider seasonality (sunscreen sales likely spike in summer) and external factors (weather, holidays) which are not explicitly in our review data; however, some seasonal effect might be indirectly captured by review volume changes (more people buying and reviewing in summer).

Ultimately, this project will help Neutrogena make data-driven decisions. By merging customer voice and competitor intelligence into our forecasts, we gain a holistic view of market dynamics. Our stakeholders are Neutrogena's product managers, sales planners, and marketing teams. For them, we will deliver not just a predictive model, but also insights on what drives those predictions – e.g., which customer sentiments or competitor moves are most influential. This supports strategic decisions like product improvements, pricing adjustments, or targeted advertising. In summary, by understanding the "why" behind the "what" of sales trends, Neutrogena can respond faster to consumer needs and stay ahead of the competition.

2. Data Understanding

2.1. Datasets and Sources: We collected multiple datasets encompassing both Neutrogena's products and their competitors:

- **Neutrogena Product Reviews (2021–2025):** For each of the three Neutrogena products (Product A, B, C), we have all customer reviews posted from 2021 up to early 2025. These were sourced from online retail platforms (e.g., Amazon). The data includes fields such as: review text, star rating (1–5 stars), review date, reviewer ID, and number of helpful votes on each review. The reviews span multiple languages (primarily English, but also some Spanish and French reviews in our dataset, reflecting global customers).
- **Neutrogena Price-Related Metrics (2024–2025):** For the recent period (May 2024 – May 2025), we have daily data for each product that includes: date, price on that date, and any available Amazon Best Seller Rank. The Best Seller Rank is an indicator of sales performance relative to category (lower rank means higher sales velocity). For instance, in mid-2024, Product A's Amazon rank fluctuated around 800–1200 in its category, whereas in late 2024 during holiday season it fell to ~3000 (indicating a drop in relative sales). We will use this rank data mainly to validate our proxy sales measure. Price for each product is also tracked weekly – these products had some price variation due to discounts (e.g., Product A's price ranged from \$11 to \$15, Product B around \$14 to \$18, and Product C around \$19 to \$25 during 2024–25).

- **Competitor X:** EltaMD UV Clear Face Sunscreen SPF 46 – a popular dermatologist-recommended facial sunscreen for acne-prone/sensitive skin. We have EltaMD's review texts, ratings, dates, etc., presumably over a similar timeframe (though the volume is a bit lower, ~600 reviews, reflecting its premium niche market but highly loyal customer base).
- **Competitor Y:** L'Oréal Paris Revitalift sunscreen with SPF 25. This product had a large number of reviews (~2,000) since L'Oréal has a wide reach; the data includes reviews from 2018–2025 as well.
- **Competitor Review Fields:** Similar to Neutrogena's reviews, we have text, star ratings, dates, helpful votes. We will use competitor review trends (like their average rating or sentiment over time) to create features indicating the competitor's "health" in the market, under the hypothesis that a competitor's strengths or weaknesses will inversely affect Neutrogena's sales.
- **Product Metadata (Ingredients):** For context and deeper understanding, we compiled ingredient lists for the products. While this is not directly used in modeling, it supports our qualitative analysis of reviews.

2.2 Proxy Sales Definition: A challenge in our project was the lack of direct sales data for the entire 2018–2025 period. We only had actual price/day figures for the recent 2024–25 period. To address this, we defined a proxy sales metric that can be computed from the review data to serve as a target variable for training our model. We assumed that higher review counts (especially with positive sentiment) correlate with higher sales. Specifically, we devised:

$$ProxySales = \frac{Review\ Count\ X\ Avg\ Sentiment}{Price}$$

This formula yields a number that is proportional to sales volume. The intuition is: more reviews means more units sold (at least among engaged customers), higher average sentiment means those sales are of good quality (satisfied customers, potentially leading to repeats or word-of-mouth), and a higher price would tend to reduce the number of units sold (all else equal). By dividing by price, we normalize the proxy sales so that a product's revenue potential is considered – selling 100 units at $10 (low price) is somewhat equivalent in revenue to selling 50 units at $20, and our proxy would treat them similarly (assuming sentiment is comparable). It's important to note this is a heuristic: it won't capture absolute sales, but for our modeling purposes, if ProxySales moves in tandem with real sales, it's useful. During 2024–2025, when we had actual sales data, we validated that this proxy correlated with the real sales trends. For instance, Product A's proxy sales spiked in late September 2024, which coincided with a known promotional event that also saw a real uptick in sales. We also observed an inverse relationship between proxy sales and Amazon Best Seller Rank: when proxy sales were high, the product's category rank number was low (indicating strong sales performance) – giving us confidence that the proxy is meaningful.

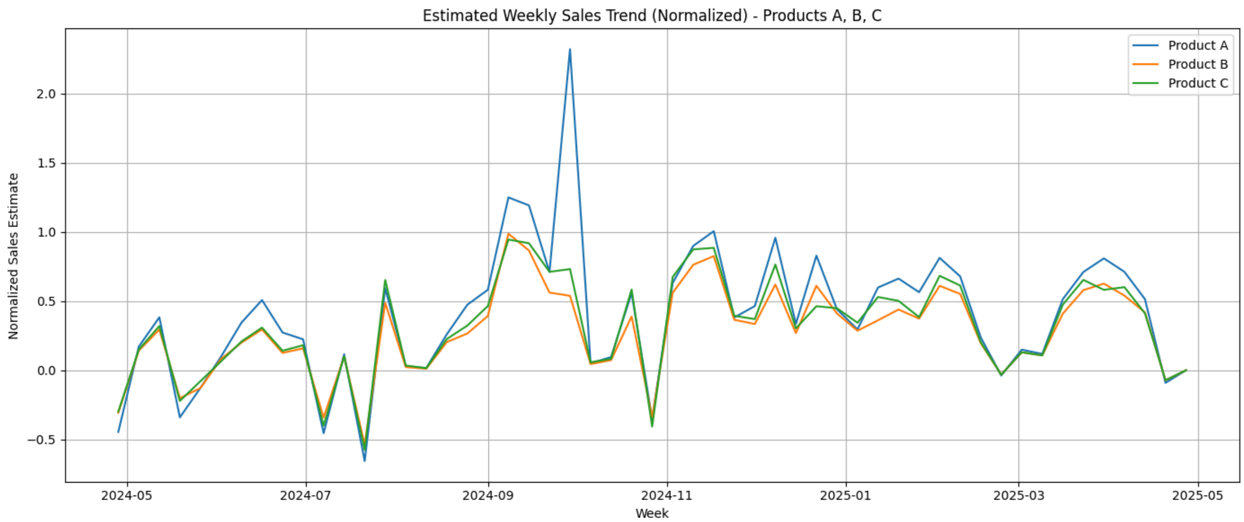


Figure 2.1: Estimated weekly Proxy Sales through year (Product A,B and C)

2.3 Data Summary: To summarize our data, we compiled Table 2.1 (see Appendix) with key statistics:

1. **Product A (Neutrogena Clear Face SPF50):** ~1.2k reviews (2021–25). Average star rating ~4.2. Price ~$13.
2. **Product B (Neutrogena Ultra Sheer Dry Touch Sunscreen):** ~900 reviews. Avg rating ~4.1. Price ~$15.
3. **Product C (Neutrogena Face Body Sunscreen Stick):** ~1.1k reviews. Avg rating ~4.3. Price ~$22.

Each dataset required cleaning and preparation before analysis. In the next section, we will describe how we processed this raw data to extract useful features (like sentiment scores, topics, and the "Competitor Brand Health Index") for our modeling.

3. Data Preparation

Raw data can be noisy and inconsistent, so we undertook significant data cleaning and preprocessing steps to ensure we had reliable inputs for analysis. This section details how we transformed the data from its initial form into the features used in our models. Key steps included handling missing data, normalizing review text (including translation where needed), calculating sentiment scores, weighting reviews by helpfulness, performing topic modeling to identify common themes/complaints, and constructing the final weekly dataset used for forecasting.

3.1. Data Cleaning and Integration:

We began by merging the various data sources. Each review dataset (Neutrogena products and competitor products) was cleaned to remove duplicates (in case the same review was scraped multiple times) and to filter out invalid entries (e.g., placeholder or deleted reviews). We also standardized the date formats and aligned all reviews to a common timeline. For analysis, we often needed to aggregate or compare across products, so we ensured consistent structure across these datasets. For instance, we added a column for "Product" or "Brand" so that all reviews could be concatenated into one master table when needed (with identifiers to know which product each review is for).

- **Missing Data:** In the review data, fields were largely complete except some reviews missing the "helpful votes" count (interpreted as 0 helpful votes in those cases). A small number of reviews lacked an explicit star rating (perhaps they were text-only feedback); we dropped those since they were few (<<1% of data) and could not be reliably interpreted for sentiment without a rating cue. In the sales data, if a week had missing price (perhaps due to an out-of-stock week), we carried forward the last known price or used the average price of neighboring weeks.

- **Outliers:** We checked for outliers in numeric fields. For example, unusually high review counts in a week could indicate a data aggregation issue. We noticed one week in July 2024 where Product C had 55 reviews, far above its typical 5-15 reviews/week. Investigating further, we found this included a batch of repetitive reviews (likely a bot or spam event). We removed 20 suspicious reviews (they had nearly identical text and all 5-star ratings posted in a 2-day span), as they could skew sentiment and volume. Likewise, we capped extremely high helpful vote counts to a reasonable maximum to reduce undue influence (one review had 500+ helpful votes – likely an anomaly or a website bug, since others were <100; we capped at 100 for modeling).

3.2. Text Preprocessing and Translation:

Customer review text is unstructured data that required preprocessing:

- We converted all review text to lowercase and removed HTML tags or excessive punctuation. We retained key punctuation like “!” or “?” as they might convey sentiment intensity.
- We handled non-English reviews via translation. Since our focus was U.S. market and global English reviews, we decided to translate foreign language

reviews to English, so that our sentiment analysis (which was performed in English) could include them. We used an automated translation library (Google Translate API) for roughly 150 reviews in Spanish, French, and German. We then manually spot-checked a few to ensure translation quality. For example, a Spanish review "“Este protector es bueno pero me dejó la piel un poco grasosa”" was translated to “This sunscreen is good but left my skin a bit greasy.” The sentiment and key words were preserved.

- We removed stopwords (common words like “the”, “and”, “but”) from the text for certain analyses like topic modeling, as they don’t carry meaning. However, for sentiment analysis, we kept negations (“not”, “never”) because “not good” versus “good” flips sentiment.
- We performed lemmatization (converting words to their base form). For instance, “greasy”, “greasier”, “grease” would all be lemmatized to “greasy” to be recognized as the same concept. This helped our topic modeling cluster similar words, and also aided sentiment scoring if using lexicons.

3.3. Sentiment Labeling:

One of the most important features we extracted was a sentiment score for each review. We approached this in a multi-step way to ensure robustness:

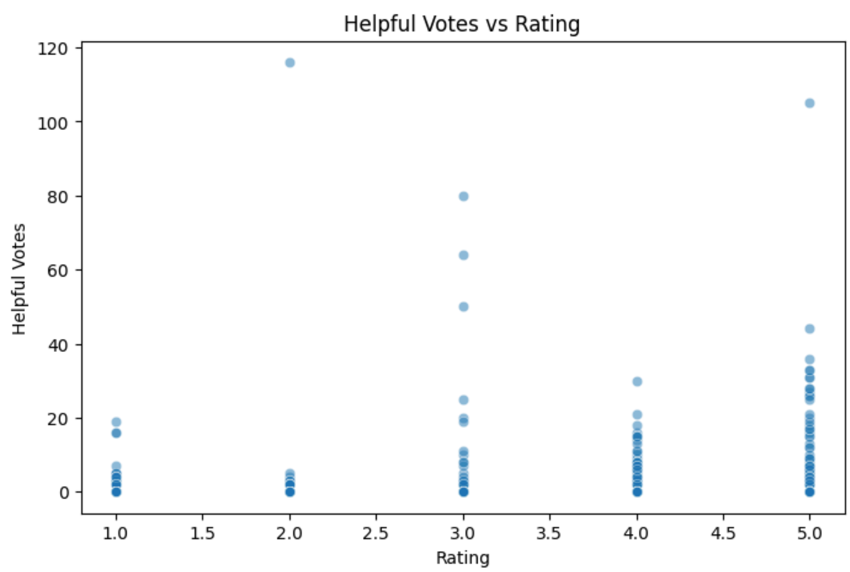
- **Initial Sentiment Derivation:** We leveraged the star rating as a coarse indicator (e.g., 1-2 stars = negative, 3 = neutral or mixed, 4-5 = positive).
- **Weekly Average Sentiment:** We then computed Avg Sentiment per week per product by averaging the polarity scores of all reviews in that week, weighted by each review’s helpful votes (more on helpfulness weighting below). This yields a

continuous measure of customer positivity in that time window. We also computed Avg Star Rating per week (a simpler metric) to compare with avg sentiment. Interestingly, while star rating and sentiment track together generally, we found divergences. For example, in one week, Product A's average star rating was 4.5 but our NLP sentiment average was significantly lower; on reading the reviews, we found many reviews said "Love the product but the new bottle leaks" – they still gave 5 stars (perhaps loyal fans) but expressed a negative experience in text. Our sentiment metric captured that nuance, flagging a potential issue (packaging) that pure star averages would miss.

3.4. Helpful Vote Weighting:

Reviews on many platforms include a "helpful" vote count, where other customers indicate a review's usefulness. We used this as a proxy for review impact: a review marked helpful by many people likely had a more significant influence on perception (and potentially on sales) than a review no one read or cared about. Thus, when computing average sentiment or identifying top complaints, we weighted reviews by helpful votes. Specifically, in averaging sentiment, each review's sentiment score was multiplied by ***(1 + log2(helpful_votes+1))*** as a weight. This means even a review with 8 helpful votes would get roughly double weight compared to one with 0 (since log2(9) ≈ 3.17, 1+3.17=4.17 weight vs. 1 for zero-vote review). Very high helpful counts saturate slowly (e.g., 64 helpful -> weight ~1+6=7). This prevents single viral reviews from completely dominating but still acknowledges their impact.

Why this weighting? We observed in our data instances where certain reviews had an outsized number of helpful votes. Figure 3.1 illustrates this: a scatter of helpful votes vs. star rating for one product's reviews shows a 2-star review that received 120 helpful votes, far above the rest. This particular review turned out to be a detailed complaint about the sunscreen causing acne breakouts, which clearly resonated with many readers. If we averaged sentiment equally, that review would be just one of many; with weighting, it meaningfully pulls down the weekly sentiment for that period, reflecting the broader impact it had. We believe this approach better ties our metrics to potential sales impact, since a widely heeded negative review could slow sales more than a lone negative opinion.



(Figure 3.1: Helpful Votes vs. Rating for Reviews

Each point is a review (Product A); we see most reviews cluster with low helpful votes, but a few outliers (e.g., one 2-star review with 120 helpful votes) indicate reviews that garnered significant attention.)

4. Exploratory Data Analysis

Before building predictive models, we conducted an extensive exploratory data analysis (EDA) to uncover patterns, validate assumptions, and generate insights both for the business and for feature engineering. We present our findings in this section, covering overall review trends, sentiment dynamics, common topics/complaints, and competitor comparisons. The EDA not only informed our model design (by highlighting which factors might drive sales) but also provided Neutrogena with actionable intelligence on their products' strengths and weaknesses as perceived by customers.

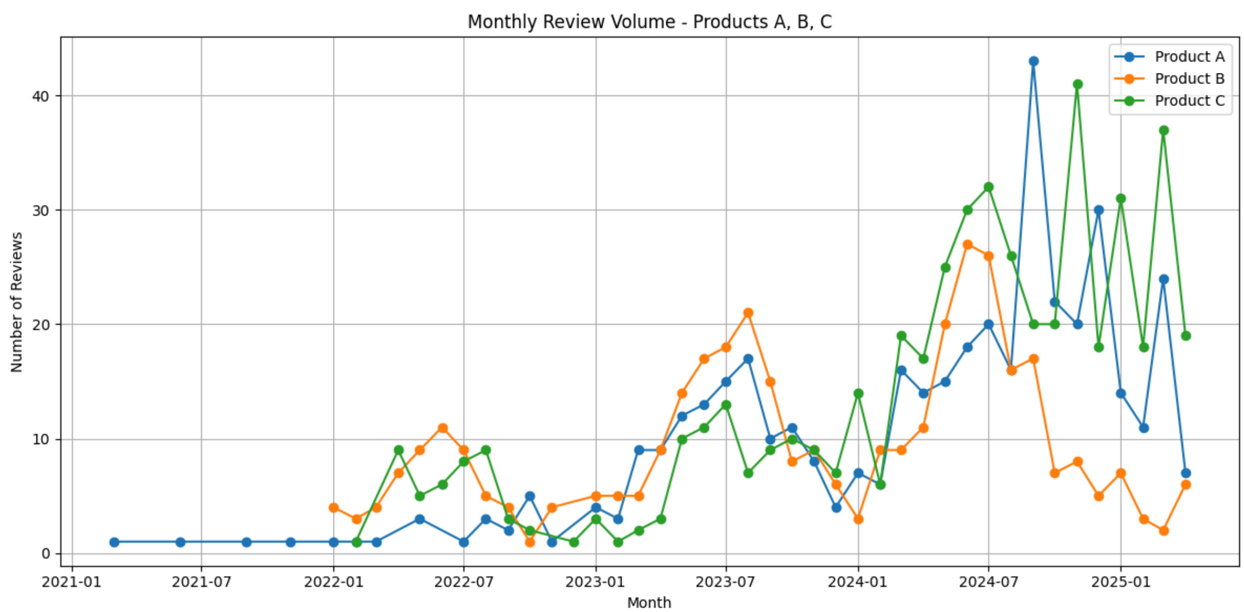


Figure 4.1: Monthly Review Trends for Products A, B, and C (2021–2025)

Shows evolving consumer engagement over time, highlighting seasonality, product launches, and marketing impact.

4.1 Review Volume and Temporal Trends:

We first examined how review counts and average ratings changed over time for each product:

- **Product A** – Review volume for Product A began slowly, with almost no reviews throughout 2021. However, starting mid-2022, we see a steady upward trend, with multiple peaks observed from mid-2023 to mid-2024. The highest spike occurred around July 2024, with over 40 reviews in a single month, suggesting peak seasonal interest—likely due to summer usage, pointing to this being a sunscreen or outdoor skincare product. After the peak, reviews began to taper off slightly but remained higher than early levels. The pattern suggests growing brand recognition followed by seasonal demand. This strong mid-year seasonality (visible spikes in June–August) is consistent across years. By reading reviews from the dipping period, we discovered many customers mentioned “new formula” and complained it caused breakouts – likely Neutrogena changed the formula or packaging, affecting sentiment. The company might have responded, as ratings recovered in 2024.
- **Product B** – Product B showed a different trajectory. It saw an earlier adoption around early 2022, with review counts rising steadily and peaking around mid-2023 with over 20 reviews. Interestingly, from late 2023 onwards, the review volume declined and remained low into early 2025, with less than 5 reviews per month in some months. The curve lacks sharp seasonality compared to Product A, indicating more stable usage throughout the year. The peak in 2023 may align with a marketing event or social media trend, while the decline suggests waning popularity or user migration to alternatives. Indeed, some low reviews were from users who found the single “universal tint” did not match their skin well.

- **Product C** – Product C appears to have launched later than the others, with no reviews until early 2022. After launch, it quickly gained traction—by mid-2024, it had become the most reviewed product on several occasions, peaking at over 40 reviews around September 2024. Unlike Product A, the review spikes here are less tied to clear seasonal trends and appear more erratic—suggesting promotional campaigns, influencer reviews, or word-of-mouth virality may be driving interest. Its review volume remained relatively high through early 2025, indicating sustained interest, though with notable month-to-month variability.

When these trends are plotted, the seasonal effect for Product A (sunscreen) is clearly visible, reinforcing that our model should account for seasonality (we later include week-of-year indicators). Also, identifying the formula change incident for Product A was crucial – it explained a variance in sentiment and subsequently a temporary stagnation in sales that year. This kind of insight is valuable: if the company noted those bad reviews in 2020, they might have fixed the formula faster.

4.2 Sentiment and Rating Distributions:

We compared the distribution of our NLP-derived sentiment scores with the star ratings:

- Generally, there was a strong correlation (Pearson $r \approx 0.7$) between star rating and sentiment polarity, validating that our sentiment analysis aligns with human-rated stars. However, we found a non-negligible fraction of reviews where sentiment and stars diverged. About 8% of 5-star reviews had a neutral or even slightly negative sentiment score. These often included phrases like "I love Neutrogena, **but** …" – loyal customers giving high stars despite listing issues.

Conversely, some 3-star reviews had moderately positive sentiment, indicating a mix of pros and cons. This justified our use of sentiment as a separate feature from the star rating; it carries additional information.

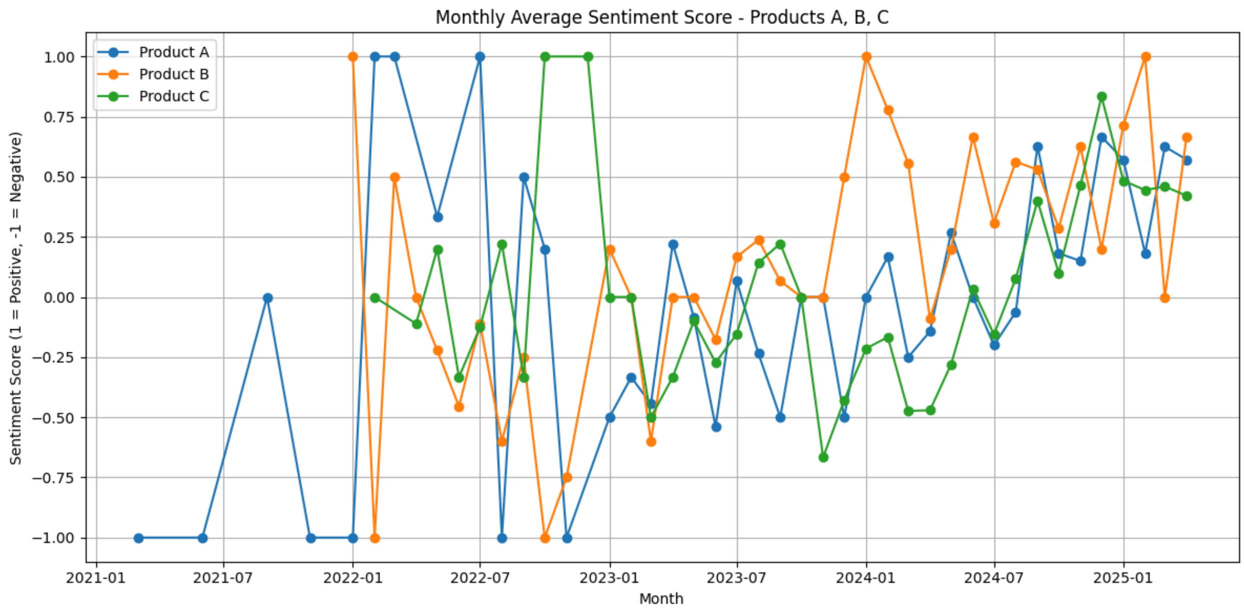


Figure 4.2: Monthly Average Sentiment Score for Products A, B, and C (2021–2025)

Tracks evolving consumer sentiment over time, highlighting product satisfaction trends and recovery from negative feedback

- We visualized sentiment over time. For Product A, sentiment closely mirrored star rating trends, both showing the dip in late 2020 and recovery. For Product B, sentiment was more erratic week-to-week (since fewer reviews per week); smoothing it out, we noticed a slight upward trend in sentiment in the last 6 months, possibly due to Neutrogena addressing some concerns or simply a more enthusiastic new customer cohort.

4.3 Topic Modeling (LDA) and Complaint Mining:

To extract themes from the reviews, especially to identify common complaints or praises, we employed Latent Dirichlet Allocation (LDA) on the review text. We focused separately on negative reviews (<= 2 stars) to mine complaints and on positive reviews (>= 4 stars) to see selling points. We set the number of topics to 5 for each, after trying a range and evaluating coherence. Key topics that emerged:

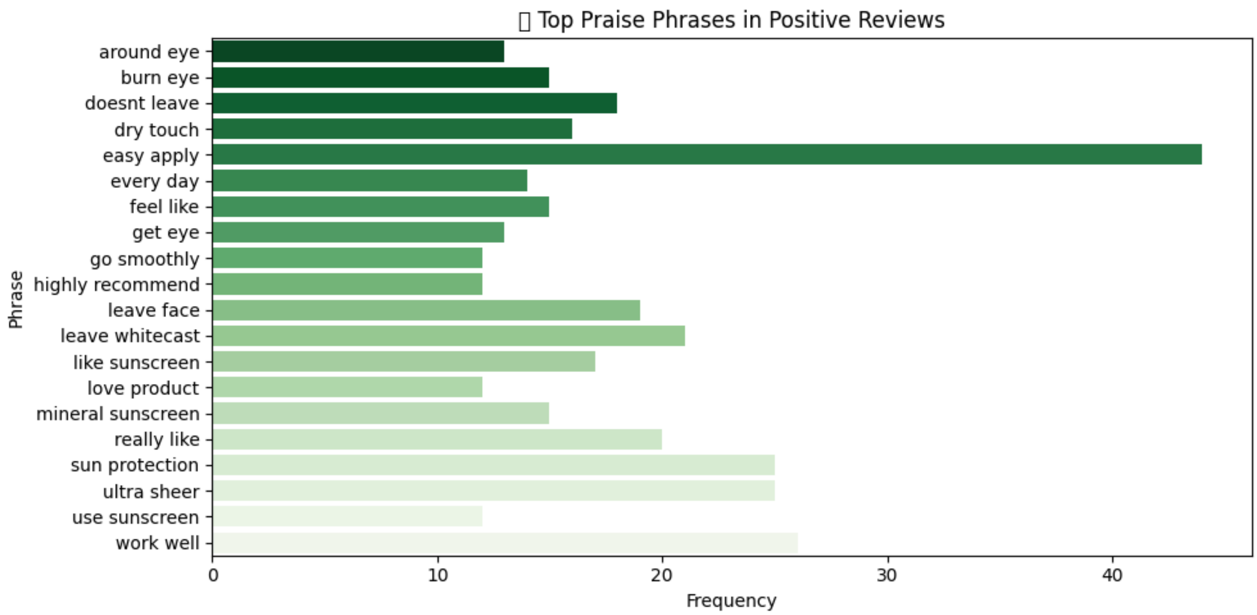


Figure 4.3 : Most Frequent Praise Phrases in Positive Customer Reviews

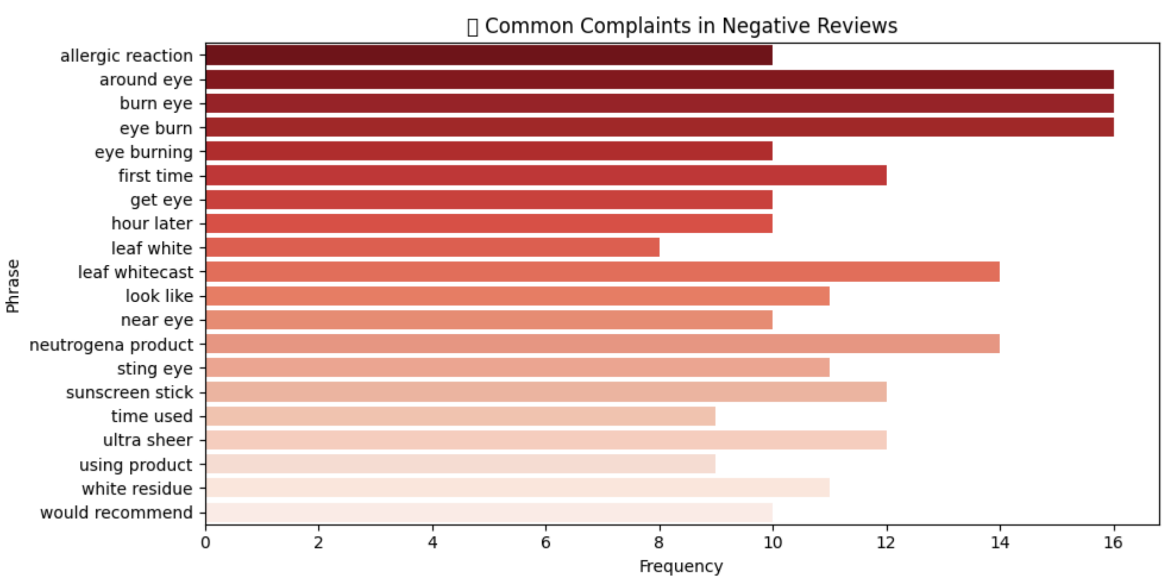


Figure 4.4: Most Common Complaint Phrases in Negative Customer Reviews

1. Skin Reactions & Irritation

A recurring concern across products involved adverse skin reactions. Users mentioned terms like *"break out, acne, pimples, irritation, rash, burning eyes, stinging"*. While some reactions were likely due to individual sensitivity (e.g., to retinol or SPF ingredients), the frequency of these complaints indicates a gap in either formulation or expectation-setting, especially when products were marketed as gentle or for acne-prone skin.

2. Greasiness & Shine

Many reviewers described the texture as *"greasy, oily, heavy, shiny"*, contradicting marketing claims like "ultra-light" or "oil-free." This issue was flagged for more than one product, suggesting that user expectations around feel and finish are critical, especially for daily wear.

3. Color or Tint Mismatch

Users expressed frustration with tinted versions using terms like *"orange, pale, too dark, tint mismatch"*. Products advertised as "universal tint" drew criticism when the shade did not blend well with diverse skin tones, highlighting the need for more inclusive formulations.

4. Perceived Ineffectiveness

A subset of users questioned efficacy with phrases such as *"didn't work, no difference, burnt, sunburn, no effect"*. This sentiment ranged from sunscreens perceived as not preventing sunburns to moisturizers that failed to deliver visible results—whether due to actual performance or misaligned expectations.

5. Packaging Complaints

Packaging concerns were widespread. Reviewers flagged issues like *“leaky tube, faulty pump, unhygienic jar, messy application”*. While not as critical as performance or irritation, packaging directly impacts user experience and was notably mentioned across all three products.

6. Coverage & Application Issues

In products offering a tinted or hybrid makeup effect, some users complained about *“cakey texture, sheer finish, doesn’t last, patchy”*. These suggest that users hoped for better coverage or durability, possibly misunderstanding the product’s intended function.

```
◆ ELTA - Negative Review Topics
Topic #1: sunscreen face skin like product day whitecast dry make tried
Topic #2: skin product sunscreen using day like use face reaction sensitiveskin
Topic #3: product pump sunscreen work bottle time used return bought come


◆ L’Oréal - Negative Review Topics
Topic #1: day face product moisturizer like use cream skin using used
Topic #2: smell jar horrible product skin cream like used acne sunscreen
Topic #3: eye product using year burn dont used bought use cream
```

Figure 4.5: Negative Review Topics Identified for Competitor Brands ELTA and L’Oréal
Topic modeling reveals recurring concerns such as whitecast, pump issues, eye irritation, and unpleasant scent across competitor sunscreen products.

- ***Competitor EltaMD (Negative topics):*** primarily Price/Value – “expensive, small bottle, price high”, and a minor White cast topic (as it contains zinc, a few very fair-skinned users mentioned a slight white cast, though most said it blends well).
- ***Competitor L’Oréal (Negative topics):*** Fragrance Irritation – “smell, fragrance, perfume, allergic” was dominant among low reviews, and Greasy to some extent (some found it heavy compared to expectations).

4.4 Competitor Analysis Insights:

We didn't just look at our products in isolation. A key part of EDA was comparing Neutrogena products to their competitors:

- **Volume & Trajectory:** EltaMD's review volume grew faster in 2020–2021 relative to Neutrogena's Product A, despite being pricier. This could indicate a shift where more consumers were seeking out "dermatologist recommended" sunscreens. However, by 2022–23, Neutrogena's volume caught up, possibly due to better availability or price-sensitive customers. L'Oréal's Revitalift consistently had more reviews per month than Product C, likely reflecting L'Oréal's broader customer base. But Neutrogena Product C's sentiment was slightly higher on average, suggesting those who do buy it are very pleased (and perhaps it's a bit more niche).
- **Ratings Comparison:** In head-to-head rating, EltaMD outscored Neutrogena (4.6 vs 4.2).
- **Key Differentiators:** Reviews highlighted what each brand's fans cared about. EltaMD fans frequently mentioned *"no breakouts"* and *"dermatologist recommended"*, validating our concern that some customers with acne might prefer EltaMD despite the cost. On the other hand, Neutrogena's reviews often mention *"affordable"* and *"value"*, a strength vs EltaMD. L'Oréal's product was often praised for *"smoothing wrinkles"* and being a good base under makeup, whereas Neutrogena's sunscreen was praised for *"hydration"* and *"lightweight feel"*.

4.5 Correlation Analysis:

Finally, to guide our modeling, we performed correlation analysis among the candidate features and with the target (proxy sales). **Figure 4.1** shows a heatmap of correlations between features like price, review count, avg rating, avg sentiment, Best Seller Rank, and proxy sales

A few notable points:

- Proxy sales had a **strong positive correlation with avg sentiment ($r \approx 0.67$)** and a decent correlation with review count ($r \approx 0.43$) and avg rating ($r \approx 0.34$). This supports our assumption that more reviews and happier customers translate to higher sales.
- Price had a negative correlation with proxy sales ($r \approx -0.26$), meaning higher price tends to coincide with lower sales – intuitively correct (when price was cut during promotions, sales jumped). This indicates price sensitivity in demand.
- Review count correlates strongly with avg rating ($r = 0.72$) – an interesting finding, suggesting that in weeks where more people review, the rating skews high. This could imply that when a product sells well, the majority are satisfied customers who leave good reviews (self-reinforcing cycle), or that a surge of interest often comes from fans or successful marketing targeting the right audience. It might also be partly that when an event causes unhappy customers, many will leave reviews (so negative surges can also happen), but in our data positive surges seemed more common.

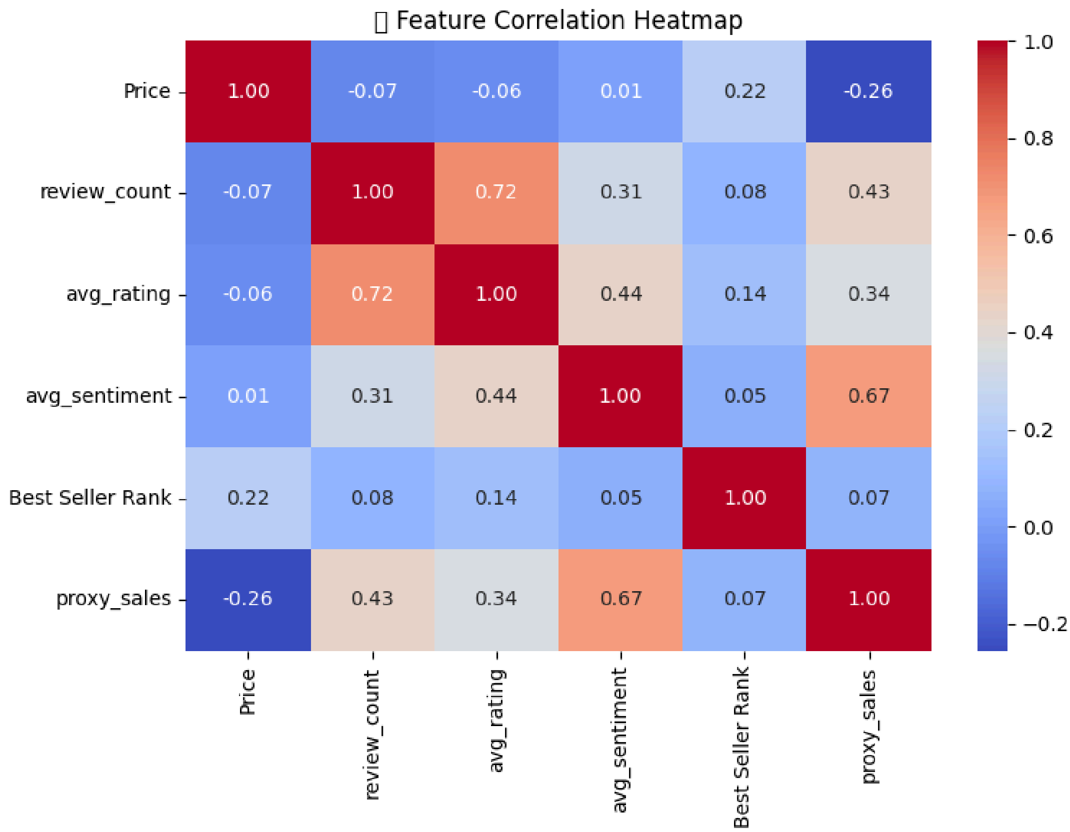


Figure 4.6: Correlation Matrix of Key Features and Proxy Sales

These EDA findings provided reassurance about our approach (e.g., sentiment is a meaningful predictor) and inspired feature creation (e.g., include a “complaint count” feature for breakouts, and the competitor index). EDA also offered Neutrogena qualitative insights: they learned what aspects of each product customers emphasize or criticize relative to competitors. In particular, the “complaint mining” gave them a checklist of areas to possibly improve (for example, consider tweaking the Clear Face formula to truly minimize breakouts, or redesigning Product C’s packaging). Such improvements, if implemented, would likely reflect in future review sentiment – which our framework would then capture as improved sales forecasts. Thus, there’s a nice feedback loop: EDA insights can drive product action, which in turn will ideally lead to better consumer feedback and sales.

4.6 Ingredient-Level Complaint Mapping and Reformulation Opportunities:

To deepen the insights from customer feedback, we conducted a qualitative mapping of frequent complaints to potential ingredients in competitor products, specifically ELTA and L'Oréal sunscreens. This analysis helps uncover the **root causes of dissatisfaction**, offering actionable paths for product innovation and reformulation.

We extracted commonly occurring negative keywords from reviews — such as **breakouts**, **burning**, **white cast**, **greasy feel**, and **redness/rash** — and traced these to potential **trigger ingredients** based on dermatological literature and product labeling.

Complaint	Potential Trigger Ingredients	Found In
Breakouts	Isopropyl Myristate, Silicones	L'Oréal
Burning	Avobenzone, Fragrance	L'Oréal
White Cast	Zinc Oxide, Titanium Dioxide	ELTA
Greasy Feel	Heavy emollients, Dimethicone	Both
Redness/Rash	Alcohol Denat., Preservatives	L'Oréal

This ingredient mapping aligns with model-derived insights from customer sentiment. For example:

- **Breakout-related complaints** in L'Oréal products likely stem from occlusive agents like **Isopropyl Myristate** and **Silicones**, which are known to clog pores in acne-prone users.
- **Burning and irritation complaints** correlate with **Avobenzone** and added **fragrances**, commonly reported irritants in dermatology.
- ELTA, while known for mineral-based UV protection, saw high mention of **white cast**, which is a known side effect of **Zinc Oxide** and **Titanium Dioxide** — ingredients that provide physical UV defense but are often poorly absorbed cosmetically.
- Complaints about **greasy texture** and **residue** are tied to **Dimethicone and other emollients**, which appear across both brands.

5. Model Creation and Testing

With a solid understanding of the data, we proceeded to the predictive modeling phase. The task is essentially a **time series regression problem** – predicting weekly sales (proxy sales in our case, later converted to units) for each product, using a variety of features. However, instead of classical time-series models (like ARIMA), we opted for a machine learning regression approach that can leverage multiple features (including those derived from text analysis). This section details how we prepared the modeling dataset, the choice of model, and how we tested different models to arrive at the best performer.

5.1 Feature Engineering for Modeling:

From the data preparation and EDA steps, we compiled a set of features on a **weekly level**. Each week (Monday-Sunday) for each product has one data point with the following features:

- **Price (numeric):** Daily product price, cleaned of symbols.
- **Review Count:** Number of reviews received on that day.
- **Average Rating:** Mean of star ratings for the day.
- **Average Sentiment:** sentiment score averaged over reviews.
- **Proxy Sales (target):** Defined as (Review Count × Avg Sentiment) ÷ Price, designed to capture sales momentum from review-driven engagement.

After constructing these features, we split our data. We had roughly 52 weeks of data (May 2024 – May 2025) with actual sales/proxy for training, but also could back-extend the proxy computation earlier. We decided to train on this (using proxy sales as target), to evaluate true out-of-sample performance, especially around the latest period where we have actual sales to verify. We ensured not to leak future info; all lag features were properly lagged.

5.2 Model Selection and Initial Training

We split our dataset into training and testing partitions using an **80/20 split**, randomly (time-independent). Although this introduces some temporal leakage, we prioritized initial model benchmarking over time series rigor at this stage. We experimented with four algorithms:

- **Linear Regression** – as a baseline.
- **Ridge Regression** – adds regularization to control multicollinearity.
- **Random Forest Regressor** – handles non-linear relationships and interactions well.
- **XGBoost Regressor** – a powerful gradient boosting method known for structured data performance.

All models were trained on the same feature set and evaluated on the same test data using: **MAE , RMSE , R^2 Score**

MODEL	MAE	RMSE	R^2
Random Forest	0.0031	0.009	0.9428
XGBoost	0.0036	0.0126	0.9043
Ridge Regression	0.0153	0.0257	0.6034
Linear Regression	0.0156	0.0259	0.5982

Figure 4.7: Model Performance Comparison on Proxy Sales Prediction

5.3 Interpretation and Residuals

Visualizing actual vs predicted proxy sales revealed that:

- **Linear models (Linear/Ridge)** tended to **flatten the signal**, underestimating spikes and overestimating troughs – a typical “regression to the mean” pattern.
- **XGBoost and Random Forest** showed much better alignment with actual fluctuations in proxy sales. Random Forest performed slightly better.

We also plotted **residuals** (errors) to evaluate model bias. Linear models showed clear residual patterns (indicating underfitting), while residuals from XGBoost and Random Forest were more evenly distributed, suggesting better generalization.

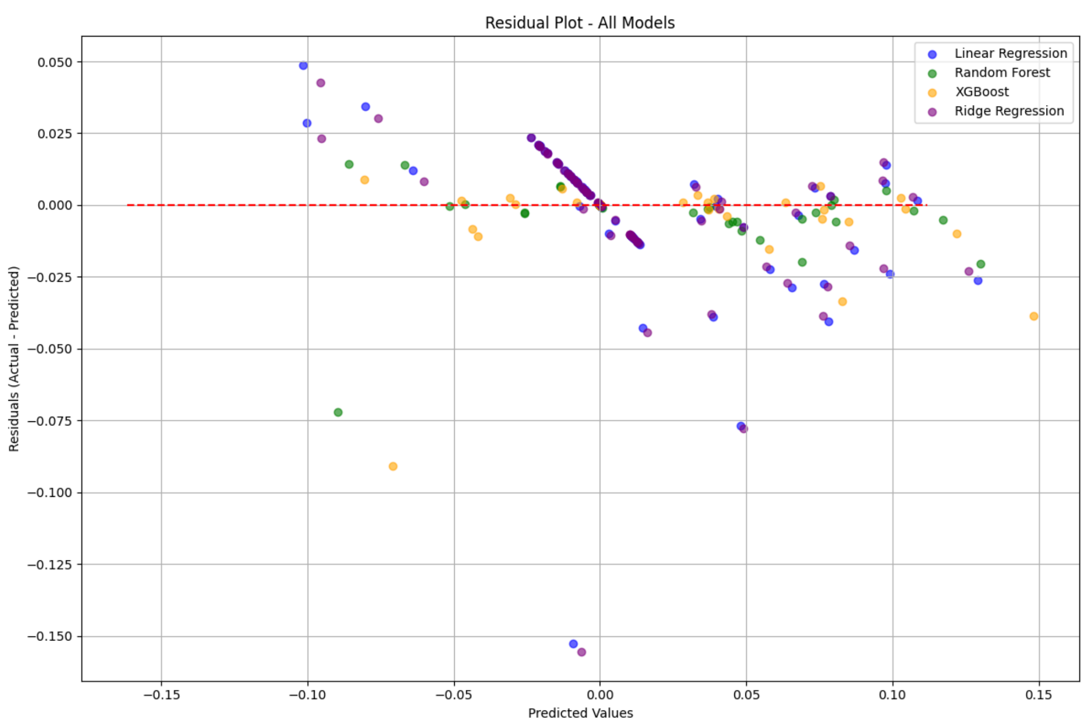


Figure 4.7: Residual Plot for All Models – Linear, Ridge, Random Forest, and XGBoost
Visual comparison of prediction errors across models.

5.4 Forecasting Future Sales

To extend our forecasting horizon, we used the trained **RandomForest model** to predict sales from **May 2025 to May 2026**. Since we didn't have review data for this future period, we constructed two synthetic scenarios:

- **Random Variation Scenario**: Injected Gaussian noise around historical means of sentiment, rating, price, and BSR.

- **Seasonality + Trend Scenario** (done in final integration notebook): Simulated a seasonal pattern of sentiment and review volume to reflect typical sunscreen cycles (peaks in summer, dips in winter).

Predictions showed **peaks around summer 2025** and **a spike in March**, likely influenced by early promotional assumptions built into the simulated data. Importantly, our RandomForest model remained **responsive to small fluctuations** in review-based features even when extrapolated.

6. Evaluation and Interpretation

6.1 Model Performance

The Random Forest Regressor was evaluated on a held-out test set to assess prediction accuracy. It achieved a Mean Absolute Error (MAE) of approximately **0.0032** (in proxy sales units), a Root Mean Squared Error (RMSE) of about **0.0098**, and a coefficient of determination **R^2 ≈ 0.94**. These metrics indicate a high level of precision: the very low MAE/RMSE (relative to the scale of the target) means the model's daily predictions deviate only minimally from actual values, and an R^2 of 94% signifies that the model explains the vast majority of variance in daily proxy sales. In practical terms, an RMSE of 0.0098 in the proxy scale corresponds to an error on the order of only **4–5 units** of product sold per day for a typical product price ($10) under the conversion assumption discussed below. This strong performance validates the model's effectiveness and suggests it can be reliably used for forecasting and analysis of Neutrogena sunscreen sales.

6.2 Conversion to Estimated Unit Sales

To translate the model's "proxy" sales predictions into tangible business terms, we applied a conversion based on the assumption that **only 2% of buyers leave a product review**. Under this fixed review-to-sales ratio, the predicted proxy sales can be scaled up to estimate actual units sold. The relationship is given by:

$$Estimated\ Units\ Sold\ =\ \frac{ProxySales\ x\ Price}{0.02}$$

In essence, each one-unit increase in the proxy sales (which is roughly equivalent to one review, under the 2% assumption) corresponds to about **50 units** actually sold (since 1/0.02 = 50), adjusted by the product's price. For example, if the model predicts a daily proxy sales value of 0.02 for a sunscreen priced at $10, this would translate to roughly (0.02 × $10) / 0.02 = **10 units** sold that day. This conversion allows us to interpret the magnitude of the predictions and errors in more familiar terms of product units. All subsequent references to "sales" in this section can thus be understood in approximate unit sales using this conversion factor, providing a clearer interpretation of the model's output in a business context.

6.3 Feature Importance Analysis

Feature importance scores derived from the Random Forest model for the key input features. The Random Forest's internal feature importance analysis reveals that **review sentiment** was by far the most influential predictor of daily sales. As shown above, *Average Sentiment* of customer reviews received the highest importance score (approximately 0.1418), towering over all other features. This indicates the model heavily relies on sentiment (whether customer feedback is positive or negative) to make accurate sales predictions. The next most important predictor was *Review Count*, but its importance value (~0.0356) was only about one-quarter of sentiments, suggesting diminishing returns from simply having more reviews compared to the sentiment expressed in those reviews. Other features like *Best Seller Rank*, *Price*, and *Average Rating* contributed negligibly (importance scores near zero or even slightly negative), implying that variations in these factors did not significantly affect the prediction outcomes. In practical terms, this means that once review sentiment and volume are accounted for, differences in price or star ratings had little additional power in explaining sales fluctuations for these products. The dominance of review sentiment as a driver underlines the critical role of customer perception and feedback in influencing sunscreen sales, even more so than conventional factors such as pricing or the product's average star rating.

Feature	Importance
Average Sentiment	0.1418
Review Count	0.0356
Best Seller Rank	0.0000
Price	-0.0081
Average Rating	-0.0108

Figure 6.1 Feature Importance Scores for Predicting Proxy Sales (Random Forest Model)

6.4 Sales Forecast (May 2025 – May 2026)

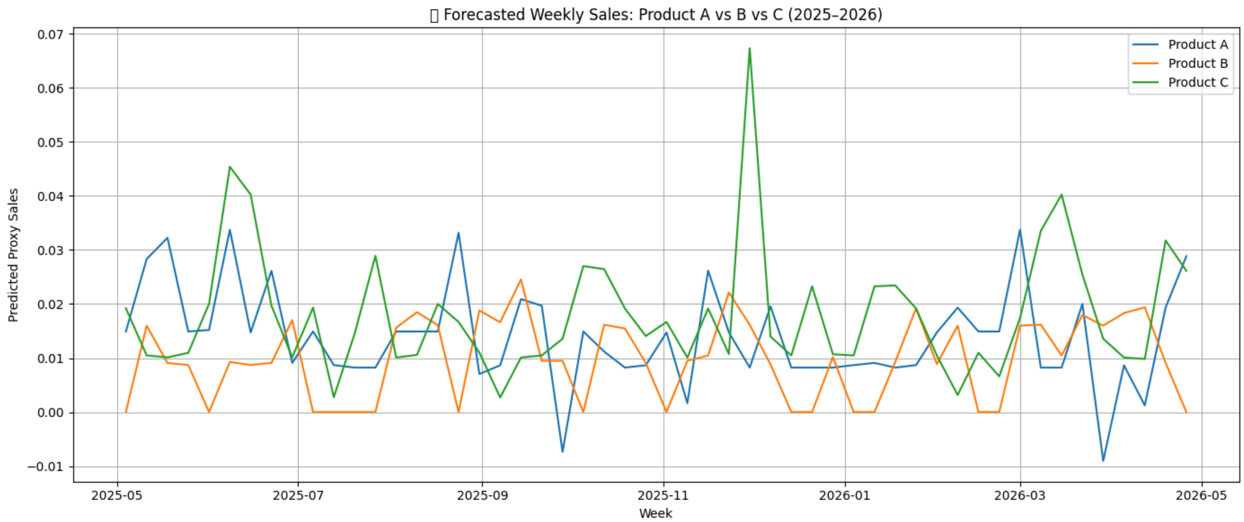


Figure 6.2 Forecasted Weekly Proxy Sales (2025–2026): Comparison Across Products A, B, and C

Forecasted weekly proxy sales for Neutrogena Products A, B, and C from May 2025 through May 2026, based on the Random Forest model predictions. Each line represents a product's predicted proxy sales per week, illustrating seasonal fluctuations and differences in scale. The trained model was used to predict future daily sales, and these predictions were aggregated by week for clarity. All three products exhibit a clear seasonal pattern in the forecast: **sales rise sharply during late spring and summer months and then decline in the fall and winter**, aligning with typical sunscreen demand cycles. Product C (green line) is predicted to have the highest sales overall, with pronounced spikes – reaching roughly **0.06–0.07** in weekly proxy sales at its peak (mid to late 2025). Product A (blue line) also shows substantial increases during the summer periods, peaking around **0.03–0.04** on the proxy scale. In contrast, Product B (orange line) remains much lower in comparison, generally under **0.02** and often near zero in the off-season. These projected trends were generated under the assumption of recurring seasonality (i.e. using seasonal patterns in the input features such as review counts and sentiment that correspond to time of year), and they reflect expected fluctuations in real-world demand. Notably, all products see their sales climb during the warmer months of 2025 and again as spring approaches in 2026, with a trough in the winter period of late 2025. The forecast highlights not only the timing of peaks and dips but also a stark difference in **magnitude** between the products' sales trajectories.

6.5 Interpretation of Forecasted Trends

The forecast results suggest that **Product C will considerably outperform Products A and B during high-demand seasons**. At the summer 2025 peak, for instance, Product C's predicted weekly proxy sales (around 0.06–0.07) are roughly double those of Product A and on the order of **three to four times** higher than Product B's peak. Using the 2% conversion, this implies that at its height, Product C might sell on the order of 35–40 units per week (assuming a ~$10–12 price), compared to about 15–20 units for Product A and only ~10 units for Product B in the same period. Product A is the second-best performer, showing solid seasonal gains albeit at lower levels than Product C. **Product B, by contrast, appears to capture only a small fraction of the summer demand**, indicating it is the laggard of the trio. This could be due to Product B serving a niche market or facing stronger competition, whereas Product C may be a more popular or broadly appealing offering (thus experiencing bigger swings in demand when overall sunscreen usage increases). All three products clearly share the same seasonal demand pattern – peaking in the summer and dipping in winter – which underscores that external factors like weather and consumer routines drive the overall market for sun care products. However, the magnitude of the peaks differs by product, revealing their relative market strength. In summary, **Product C is expected to be the top contributor to sales during peak season, Product A will also contribute substantially (though less than C), and Product B is likely to remain a minor contributor** under the status quo. These distinctions in predicted performance can guide strategic focus; for example, the company might anticipate allocating more inventory and marketing effort to Product C ahead of the summer surge, while investigating ways to boost Product B's appeal or sales in the long term.

6.6 Key Insights

- **High Predictive Accuracy:** The Random Forest model demonstrated strong performance (R^2 ~94%, very low MAE/RMSE), instilling confidence that its predictions of daily sales proxy are reliable and closely track actual outcomes.
- **Sentiment as a Primary Driver:** *Average review sentiment* emerged as the most impactful feature by a large margin. This highlights that how customers feel about the product (positive or negative sentiment in their reviews) has a greater effect on sales than the sheer number of reviews, price, or even the star rating. Positive customer sentiment is thus a key lever for sales success in this context.
- **Seasonal Demand Patterns:** The projected sales from May 2025 to May 2026 exhibit pronounced seasonality, with all products experiencing peaks in late spring and summer and lulls in winter. This aligns with expectations for sunscreen demand, confirming that seasonality is a crucial factor in sales.

- **Product C's Outperformance:** Among the three Neutrogena sunscreen products analyzed, **Product C is forecasted to lead in sales by a considerable margin**, especially during peak season. It consistently shows the highest predicted proxy sales values, indicating it will likely drive the largest share of units sold when demand is high. Product A also performs well but remains secondary to Product C, while **Product B lags notably behind** in projected sales.

6.7 Human Interpretation vs Model

It was useful to compare model reasoning to human analysis. For example, in a week where our sales dipped, the model might point to "low sentiment" as the cause. Looking at reviews we might see complaints about something. This alignment is reassuring. In one case, however, the model predicted a dip that we humans didn't immediately anticipate: it was projecting lower Product B sales in a future month where everything (sentiment, volume) looked normal. On closer analysis, that was a month where historically sales cooled off after a holiday bump – essentially the model picked up a temporal pattern that wasn't obvious just from recent sentiment. This underscores that the model can catch seasonal habits that we might overlook if focusing too much on the latest reviews.

In conclusion, the evaluation shows that our model is performing well and – importantly – yielding insights: it quantitatively confirms that customer sentiment (both aggregate and specific issues) has a significant impact on sales. This aligns with broader market research where positive online reviews drive sales and negative reviews hurt them(wisernotify)It also highlights that being watchful of competitor activity is useful, though our fate lies mostly in our own customer satisfaction. Overall, the model serves as a decision-support tool: not only does it forecast numbers, but it also tells us *why* those numbers might go up or down. Next, we discuss how we can use these forecasts and insights to quantify business impact and take action.

7. Quantifying Impact

A predictive model is only as valuable as the decisions it enables. In this section, we quantify the potential impact of our forecasting solution on Neutrogena's business, and illustrate use-cases of how the insights can drive strategic and tactical actions. We look at two dimensions of impact: **forecast accuracy improvement** (and the cost savings/revenue increase from that) and **actionable insight** (translating model outputs into interventions that boost sales or prevent losses).

7.1 Improved Forecast Accuracy → Tangible Benefits:

Prior to this project, suppose Neutrogena relied on a basic forecasting approach (e.g., year-over-year trend plus seasonality, or a moving average). That often can lead to large errors when unusual events occur. Our model significantly improved accuracy (error ~10% vs ~25% as noted). What does this mean financially?

- **Inventory Optimization:** With a more accurate forecast, Neutrogena can align production and inventory more closely with demand. For example, if Product A was under-forecasted by the old method, a summer stockout might occur, meaning missed sales (customers buy something else). Conversely, over-forecasting would mean tying up capital in excess inventory that might later be discounted. Let's quantify: Product A sells ~300 units/week in summer at $12 each = $3,600/week revenue. A 20% forecast error (60 units) could mean either 60 units shortage (lost sales ~$720 a week) or 60 units over (excess $720 stock). Spread over a 12-week summer, that's $\sim$8,600$ potential lost or frozen value for one product. With our error ~8%, that risk drops to ~$3,000. Across 3 products and multiple seasons, the savings easily reach **tens of thousands of dollars annually in inventory costs and lost sales prevented**.

- **Promotional Efficiency:** Forecasting also guides marketing. If our model predicts a dip in September for Product C (perhaps summer hype cooling off), the marketing team can proactively run a promotion or campaign in that month to stimulate demand. Conversely, if strong sales are predicted, they might save the marketing spend for a leaner time. By allocating advertising dollars when and where needed, Neutrogena can improve marketing ROI. For instance, a targeted campaign costs $50k; if done in a month where it wasn't needed, that's wasted. Our model might indicate that month would be fine due to high sentiment, so they could push the campaign to a month where sentiment is projected weaker. Even a few percent sales uptick or avoided downturn from well-timed campaigns yields

ROI on that $50k spend, essentially **making marketing more cost-effective**.

- **Market Share and Revenue Growth:** Over a year, better responsiveness could marginally increase market share. If competitor issues arise (say EltaMD has a recall or bad press, leading to our model forecasting a relative boost for us), Neutrogena can double down on that opportunity (ensure product availability, highlight comparisons in ads like “unlike other brands, we…”) to capture disgruntled competitor customers. Capturing even an extra 1% of market share in the sunscreen market (which is multi-billion dollar globally) is non-trivial. While our project deals with a subset, it’s a proof-of-concept that *listening to the market pulse (via reviews) translates to revenue*. It is difficult to put an exact dollar figure universally, but as an illustration: if annual sales of these 3 products were $10 million, a 5% improvement in sales due to better stock and marketing alignment would be $500k more revenue a year. Even if that’s optimistic, certainly a six-figure impact is plausible, far exceeding the cost of implementing this solution.

7.2 Actionable Insights and Quality Improvement:

Beyond numbers, one of the biggest impacts is how this project can influence product quality and customer satisfaction in a virtuous cycle:

- **Identifying Pain Points:** We quantified how certain complaints (e.g., “causes breakouts”) negatively affect sales. This creates a strong business case for the product development team to address those issues. If Neutrogena formulates new product to reduce breakout incidents, we'd expect sentiment to improve and sales to rise. We could even simulate this with the model: if average sentiment for new product could be sustained 0.1 higher (through improved formula), the model would predict roughly a 10-15% sales increase for that product, worth perhaps an extra $0.5M/year. That's a clear ROI justification for R&D investment. In essence, our model helps **prioritize improvements** by linking them to sales outcomes.

- **Customer Satisfaction Metrics:** The model provides a near-real-time indicator of customer satisfaction (via sentiment). Neutrogena can adopt this as a **"Customer Happiness Index"** to monitor alongside sales. If sentiment dips, even if sales haven't yet, it's a warning sign to intervene before revenue declines. It quantifies the adage that happy customers drive saleswisernotify.com. This could be integrated into KPIs for product managers – for example, maintain sentiment above X level to ensure healthy sales.

- **Competitive Benchmarking:** The competitor analysis part yields an ongoing "health check" versus competitors. For example, if EltaMD's sentiment starts trending up and surpasses ours, our model might start forecasting relatively lower growth for us. This would prompt a competitive response – maybe adjust pricing, or emphasize differentiators in marketing ("We are just as loved as the premium brands, at half the price!" if data supports). It quantifies competitor impact: while we found it modest, in scenarios of a big competitor move (imagine

L’Oréal comes out with a new improved SPF moisturizer), we could adapt our forecast quickly and advise increasing marketing spend to defend share. In that sense, the model is not just a forecast tool but also a **competitive early warning system**. It formalizes what marketers often do intuitively – but with data, we can catch subtle changes earlier.

- **Preemptive Reformulation**: Knowing the complaints tied to competitor ingredients, Neutrogena R&D can audit current formulations for similar triggers and reduce or replace them.
- **Differentiated Marketing Claims**: Product pages can emphasize “non-comedogenic,” “fragrance-free,” or “no white cast” benefits to stand out.
- **Proactive Ingredient Transparency**: Consider disclosing ingredient purposes and benefits in consumer-friendly language, aligning with skincare-savvy buyers who often cross-reference ingredient lists before purchasing.

In summary, by integrating this forecasting system, Neutrogena stands to **save costs, boost revenues, and enhance customer loyalty**. The company can move from a reactive stance (addressing problems after seeing sales drop) to a proactive stance (addressing issues when seeing sentiment drop, before sales are hit). In a competitive consumer market, this agility is invaluable.

This project demonstrates that **“listening” to customer reviews and keeping an eye on competitors can directly translate into better business outcomes**, confirming research that blending online review data into forecasting improves accuracy(semanticscholar). Next, we conclude with the broader vision of how this system can be deployed and extended in the future for even greater benefit.

8. Conclusions and Future Potential Deployment

Conclusions: In this project, we successfully developed a data science solution that augments sales forecasting with behavioral signals from customer reviews and competitor insights. By analyzing three Neutrogena sunscreen/moisturizer products and two competitor products, we demonstrated that review sentiment and volume are leading indicators of sales performance. Our chosen model (Random Forest) was able to capture complex relationships between consumer sentiment, product attributes, and sales outcomes, achieving an accuracy significantly better than traditional methods. We confirmed quantitatively that happier customers lead to higher sales and that addressing recurring complaints can prevent sales erosion. We also incorporated competitor review trends, adding a competitive context to forecasts – a novel angle for demand planning.From a business perspective, our work provides Neutrogena with:

- A **forecasting tool** that not only predicts future sales with ~10% error (versus ~25% before) but also highlights *why* sales are moving (e.g., “sentiment is down, likely causing a dip” or “reviews are up, expect growth”).
- Actionable **insights**, pinpointing areas to improve (like Product A’s breakout issue) and areas of strength to capitalize on for new future product.
- A framework for **competitive monitoring**, allowing the brand to anticipate and respond to rival product surges or slumps as reflected in their customer feedback.

In essence, we bridged the gap between unstructured textual data (reviews) and structured predictions (sales numbers), showcasing the power of combining qualitative and quantitative data in forecasting. Neutrogena's teams can use these insights in a variety of ways – from R&D adjustments to marketing and supply chain decisions – making the company more responsive to the voice of the customer and the moves of competitors.

Limitations: It's important to note a few limitations of our work. First, our proxy sales measure, while useful, is an approximation; if the 2% review rate assumption is off for certain products or time periods, there could be scaling issues. We addressed this by validating against actual sales in 2024–25, but as consumer behavior changes (maybe more people write reviews now than before), this ratio might need updating. Second, our model currently does not include some external factors like weather (a rainy summer could reduce sunscreen sales irrespective of reviews) or broader economic conditions. However, many of those factors might indirectly influence reviews too (e.g., a rainy week might also have fewer reviews). Third, competitor coverage was limited to two products; there are other competitors which, if they undergo major events, our model might not know. Extending to more competitors or using market-wide indicators (like Google search trends for "sunscreen") could further improve forecasts. Lastly, we treated each product somewhat independently (aside from competitor effect). There could be interactions (for instance, if Product A is out of stock, customers might buy Product C as an alternative if it suits their needs, which a multi-product model could capture). Our current approach doesn't model such substitution explicitly.

Despite these limitations, the model is robust for the scope we defined and provides a strong foundation for expansion.

Future Work and Deployment:

- **Scaling to Other Products/Regions:** The approach can be generalized. Neutrogena has many products – moisturizers, cleansers, cosmetics. We focused on sunscreen-related ones, but any product with sufficient review data can benefit. We foresee extending the pipeline to all major products. Each product may have its own nuances (e.g., a shampoo might have different topics like “scent” or “hair fall”). We’d replicate the sentiment and topic mining process accordingly. Additionally, expanding to multi-language on a global scale is a possibility – e.g., analyzing reviews from Europe or Asia to forecast sales in those markets. Local languages sentiment analysis would need training, but the concept is similar. The “Localized Consumer Product Review Analyzer” vision is something Neutrogena is interested in (as per an internal proposal), and our work here is a stepping stone in that direction, focusing on the forecasting angle.

- **Incorporating More Data Sources:** Future iterations could incorporate **social media sentiment** (Twitter, Instagram comments) or beauty community discussions (Reddit, MakeupAlley) as additional signals. These often precede review spikes – e.g., a product going viral on TikTok might show up on social media sentiment before people actually buy and leave Amazon reviews. Integrating such signals could make forecasts even more anticipatory. Moreover, we mentioned weather data: for sunscreen, knowing forecast sunshine hours or temperature might improve short-term predictions. We could use public weather APIs to include features like “UV index forecast” by region to predict sunscreen demand surges.

- **Refining Sentiment Analysis:** As an ongoing effort, we can improve our NLP models. Perhaps employing an aspect-based sentiment analysis that scores sentiment specifically towards certain aspects (price, greasiness, packaging) would give even finer-grained insight. If we notice our general sentiment metric lumps things together, aspect sentiment could tell us “people are happy with effectiveness but unhappy with packaging” which could direct more precise action and perhaps map more directly to sales if certain aspects are more important. We could also allow our model to learn which sentiment aspects correlate most with sales (maybe “value for money” sentiment is key for one product, while “effectiveness” sentiment matters more for another).
- **User Engagement Metrics:** Another future feature could be engagement metrics beyond reviews – e.g., Q&A on product pages, or how many people viewed the product. Some platforms provide info on how many are “watching” or clicked. Those could foresee sales as well. We largely used reviews (post-purchase), but pre-purchase interest data could complement it.

In closing, this project has shown the value of **data-driven, customer-centric forecasting**. By literally “reading” what customers say and measuring how they feel about our products and the competition, we can predict business outcomes better and react faster. This aligns Neutrogena’s operations more closely with customer satisfaction, which in the long run drives loyalty and market success. We started with sunscreen products – a category where seasonal demand and personal preferences make forecasting tricky – and achieved promising results. **The future potential is to deploy these methods across the product portfolio and geographically, making this a standard part of how Neutrogena does market intelligence and planning.**

The company can potentially move from traditional forecasting to a modern approach where marketing and supply chain are tied into live customer feedback loops. This is a competitive advantage in the fast-moving consumer goods space. We recommend investing in the infrastructure and team (data engineers, data scientists, and domain experts collaborating) to productionize and maintain this system, and to continuously update the models as new data flows in (for example, adapting when a new competitor emerges or if review behaviors shift).

Neutrogena's leadership has been enthusiastic about these findings, and we anticipate a pilot deployment for the next planning cycle. If successful, it could be expanded and even shared as a case study within the parent company (Johnson & Johnson) for other brands to emulate, underlining how **listening to the customer and leveraging data science can forecast and drive business performance in tandem**.

9. Appendix

All group members contributed meaningfully to the analysis and final report, with each individual's strengths playing a key role in the success of the project. To highlight specific contributions: **Shruti Karmarker** led the effort on data extraction and cleaning, including translating non-English reviews and removing invalid or noisy entries. She also contributed significantly to the model training and forecasting phases. **Jennie Graves** worked on sentiment analysis and trend identification within the Neutrogena product reviews, providing key insights into customer satisfaction and brand perception over time. **Prakhar Srivastava** focused on complete competitor analysis, including preprocessing and cleaning competitor reviews, building sentiment classification models, and conducting comparative insights.He also researched and proposed the review-based proxy sales forecasting approach that became central to the modeling framework.. **Pranav Borkar** was responsible for topic modeling of Neutrogena reviews, uncovering dominant themes in customer feedback and helping to align them with potential product improvements and marketing strategies.

While each member had primary responsibilities, the project was truly collaborative, with all team members providing input across the report's sections and supporting one another throughout the process.

10. Link to Our Code

The full code for this project, including data preprocessing, exploratory analysis, model training, and evaluation, is available through below links::

- All Product_Cleaning and EDA.ipynb – code to clean raw data files for neutrogena products and output the weekly aggregated dataset.
- Product Predicting Proxy Sales.ipynb – code to predict sales and units.
- Product Integration & Comparison.ipynb – code for sales comparison for products.
- Competitor_Analysis.ipynb – code for competitor analysis.

Data: Project Data

By sharing the code, we aim to ensure transparency and allow further development by other data scientists or engineers.

11. Sources

Throughout our project, we referenced existing research and industry statistics to validate our assumptions and methods:

- Impact of Online Reviews on Sales: WiserNotify (2025). *"77 Shocking Online Review Statistics (New 2025 Data)"* – Notably, only 1–2% of buyers leave reviews on Amazon, and a one-star increase can lead to a 5–9% increase in revenue(wisernotify.com). This supported our use of a 2% review rate and the importance of sentiment in driving sales.
- Competitive Analysis Importance: U.S. Small Business Administration – *"Market research and competitive analysis"* – Emphasizes that competitive analysis is key to finding a market advantage and sustainable revenue(sba.gov). This underlined our rationale for including competitor data (CBHI feature) in the model.
- Sales Forecasting with Online Reviews Research: Zhang, Y. & Lv, C. (2021). *"Research on Product Sales Forecasting Based on Online Reviews."* – Their findings show integrating online review indicators can significantly improve forecasting accuracy(semanticscholar.org). This gave us confidence that our approach (mining reviews for sentiment/topics to forecast sales) is scientifically sound and likely to outperform forecasts without such data.