Tracing Consumer Emotion Over Time: A Clustered Sentiment Analysis of Amazon Electronics Reviews

Hartejh Surikapuram

Abstract

This project explores how consumer emotion in Amazon electronics reviews changed over time by analyzing patterns in written sentiment between 2010 and 2017. The primary objective was to move beyond static or binary sentiment classification and instead trace emotional evolution across product categories and user concerns. The analysis used the Amazon Electronics Reviews dataset, comprising 12,773 reviews after preprocessing. BERTopic was applied to extract 163 initial topics, which were then grouped into 15 broader clusters using hierarchical clustering; six clusters were selected for detailed emotional analysis based on semantic coherence and emotional richness. Emotional trends were quantified using the NRC Emotion Lexicon, which maps words to eight basic emotions and two polarities. Visualizations such as stacked bar charts, radar plots, and line graphs were employed to reveal emotion drift over time. A TF-IDF approach further identified emotion-specific terms during early (2010–2013) and late (2015–2017) periods to uncover shifts in emotional vocabulary. While the overall emotional tone remained largely positive and stable across the dataset, individual clusters revealed subtle yet meaningful shifts. For example, reviews related to customer support showed increased anticipation and frustration, and experienced sharp rises in negativity. These patterns indicate that platform-wide emotional stability may obscure important fluctuations within specific product categories. The analytical framework developed in this study enables the detection of nuanced emotional changes in online electronics reviews, offering a deeper understanding of how emotional expression shifts across both product categories and broader thematic groupings over time. By capturing these shifts, the analysis reveals emerging concerns, changing expectations, and evolving user experiences that would be overlooked in high-level sentiment summaries, helping to contextualize feedback, surface latent issues, and trace the development of emotional narratives within consumer discourse.

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Introduction

Customer reviews are a critical source of feedback in the digital marketplace, shaping not only individual purchasing decisions but also broader perceptions of product quality, reliability, and customer service. In the electronics sector, where products are often technical, high-cost, and rapidly evolving, reviews provide detailed insights into user experiences that go beyond what is captured by star ratings alone. The emotional tone embedded in reviews can reveal patterns of trust, frustration, and satisfaction that may not be immediately visible through quantitative ratings.

Despite the widespread availability of review data, relatively little attention has been given to how these emotional tones evolve over time across types of products and user concerns. Most existing analyses treat sentiment as a static attribute, overlooking the dynamics of consumer emotion. Capturing these dynamics is particularly valuable in identifying systemic issues, tracking perception of certain products, and informing product development and customer support strategies.

This paper presents a multi-layered analysis of Amazon electronics reviews, focusing on how emotional tone changes over time within semantically meaningful product-based groupings (e.g., charging accessories, remotes) and thematic groupings (e.g., customer support, durability). The analysis begins by applying BERTopic to extract review topics, followed by hierarchical clustering to group related topics into broader thematic clusters. Emotional trends are then quantified using the NRC Emotion Lexicon, enabling visualization of how consumer sentiment shifts within each cluster over time. This approach provides a nuanced understanding of both the structure and emotional content of user feedback in a fast-moving consumer technology landscape.

The remainder of this paper is organized as follows: the next section outlines the dataset, and details the data collection and analytical methods used. This is followed by a presentation of key results, with a focus on temporal emotion trends within the identified product and thematic clusters. The paper covers the implications of these findings for and concludes by outlining key limitations and suggesting directions for future research.

Related Works

Several studies have focused on technical advancements in sentiment classification, particularly through the application of machine learning and deep learning. Ghatora et al. evaluated the effectiveness of both traditional machine learning algorithms and large pre-trained language models (LLMs) in classifying product reviews by sentiment polarity. Their results show that LLMs like BERT outperform older models, supporting the growing use of transformers in natural language processing tasks. Similarly, the SpringerOpen article investigates supervised ML techniques applied to contemporary product reviews, emphasizing preprocessing strategies and model performance. While more limited in scope, it contributes practical insight into sentiment classification pipelines. Both studies prioritize predictive accuracy over interpretive insight, and neither explores how emotional patterns evolve over time or differ across product types.

Other research integrates sentiment analysis into functional applications that provide personalized suggestions to users based on their past behavior. Reddy et al. design a sentiment-driven recommendation engine that uses opinions extracted from reviews to inform product suggestions. Their approach emphasizes the value of sentiment analysis, by enhancing user experience through personalization. However, like the previous works, their focus remains largely technical, with minimal attention on emotional nuance or cross-category sentiment dynamics.

Daza et al. offers a bibliometric and systematic review that maps the evolution of sentiment analysis methods in e-commerce. By cataloging algorithms, datasets, evaluation metrics, and challenges, they provide a high-level overview of research trends and future directions. Although not empirical in the conventional sense, their work situates sentiment analysis within the broader trajectory of computational research. David Kyn’s project demonstrates how to use simple tools like VADER and

TextBlob to analyze customer sentiment. It reflects growing public and commercial interest in applying sentiment analysis techniques to real-world brand and product perception.

Adiat Urbano's article implemented the use of sentiment classification using machine learning techniques, and text vectorization methods such as TF-IDF. They use Natural Language Processing (NLP) machine learning model and also applied a Transformer based RoBERTa model to understand the sentiment of users towards a product using reviews in order to understand the relationship between emotion and star ratings given by the user on Amazon products as well as Yelp reviews.While it does have a similar approach to us, this approach emphasizes on prediction accuracy over or emotional depth. It does not consider sentiment throughout the timeline of early to late Amazon and does not go in depth into nuanced emotions like joy, trust, or anticipation.

By contrast, our project builds on this foundational work by moving beyond simple polarity classification. Instead of treating sentiment as static or binary, we analyze how emotional tones evolve over time (2010–2017) and vary across product-related clusters. Incorporating the NRC Emotion Lexicon and TF-IDF weighting, our study highlights not only what users feel, but also *why* and *how* their emotional expressions shift in relation to changing topics or events. This allows us to uncover patterns of emotion drift, topical evolution, and emotional stability that are largely overlooked in past sentiment classification pipelines like Urbano's.

From these works, we know that machine learning methods can effectively classify sentiment in product reviews. It is clearly emphasized on how sentiment is useful for understanding customer satisfaction and informing business decisions.

Some clear gaps are about how emotional tone in reviews changes over time, particularly during key stages of a platform's growth. Most research treats products as a uniform group, without exploring how emotional expression varies across product categories or thematic groupings. They leave out sentiments that explore more nuanced emotional patterns (trust, anticipation, anger).

Our study adds more depth by contrasting sentiment across specific product categories within electronics, analysing whether emotional tone patterns are consistent across broader thematic groupings. This allows us to compare different product categories and see if emotional tone stays the same across broader themes, or if it changes depending on the type of product. Rather than improving predictive performance, our study looks at how emotional tone changes over time and across different types of products to better understand customer feelings. Our approach uses sentiment analysis to uncover historical and cultural patterns in user behavior on Amazon.

Data and Methods

To conduct the analysis, this study utilized the Amazon Electronics Reviews 2018 dataset available on Kaggle. The dataset contains 19,809 customer reviews spanning from August 25, 2000, to September 24, 2018, covering a broad range of electronic products such as laptops, speakers, chargers, and other devices. Each entry includes key attributes such as reviewText (the main body of the review), summary (a brief headline), reviewTime (the date the review was posted), overall (a 1–5 star rating), and vote (number of helpful votes). This dataset was extracted from the larger Amazon Review Data (2018) corpus compiled by Jianmo Ni at UC San Diego. Although it was released in conjunction with a 2019 EMNLP paper by Ni, Jiacheng Li, and Julian McAuley, the electronics subset was not directly analyzed in that publication and was instead provided as a public resource for the research community.

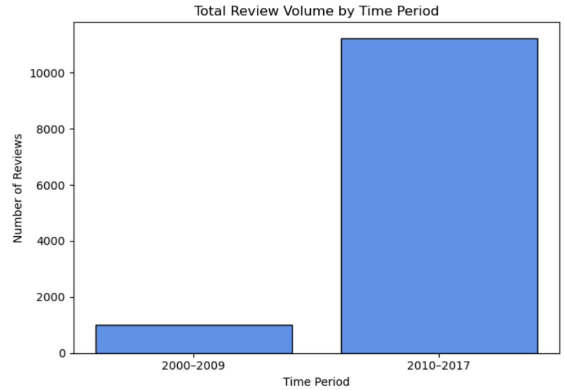

Figure 1: Review Volume by Time Period

For the purposes of this analysis, only reviews from 2010 through 2017 were retained. Earlier reviews were excluded due to data sparsity, and 2018 was excluded because the dataset did not cover the full calendar year, which could bias time-based trends.

Two additional variables were engineered: reviewLength, representing the number of words in each review, and Year, extracted from the reviewTime field to enable time-based analyses. Initial preprocessing involved filtering out reviews with fewer than five words in the reviewLength field, reducing the dataset size from 19,809 to 12,773 entries. No missing values were detected across the dataset, so no imputation was required. Text preprocessing was performed using the Natural Language Toolkit (NLTK), which included converting all text to lowercase, removing punctuation, special characters, and stop words, followed by lemmatization using WordNetLemmatizer. These steps ensured consistency in word representation and improved the quality of the analysis.

To assess emotional content, the NRC Emotion Lexicon was employed. This lexicon maps English words to eight basic emotions: anger, anticipation, disgust, fear, joy, sadness, surprise, and trust as well as to binary sentiment polarities (positive and negative). The lexicon was converted into a DataFrame format to facilitate efficient lookups and integration with the cleaned text data. Each review was then tokenized and evaluated against this lexicon, enabling a nuanced assessment of emotional tone and sentiment across time, product categories, and thematic clusters derived from topic modeling.

For topic modeling, the BERTopic framework was applied to the cleaned reviews. BERTopic combines BERT-based document embeddings with class-based TF-IDF and HDBSCAN clustering to generate interpretable topic groupings. This process identified 163 unique topics across the dataset. However, many of these topics were too sparse or narrow in scope to support deeper emotional or thematic interpretation. To address this, hierarchical clustering was applied to the topic embeddings and a linkage matrix was constructed based on pairwise distances between topic vectors. The fcluster function was then used to cut the resulting dendrogram into 15 clusters using the “maxclust” criterion. Each topic was mapped to its new cluster assignment, and a new column, cluster_fixed15, was added to the dataset to reflect these groupings.

Out of the 15 resulting clusters, six were selected for in-depth analysis based on semantic coherence, review volume, and emotional richness.

Final Cluster Overview

Cluster	BERTopic Label	Assigned Label	Top Keywords
Cluster 1	plug_screen_customer_customer service_service	Customer Support & Usability	customer, service, screen, plug, support
Cluster 3	connection_port_macbook_broke_connect	Computer Accessories & Ports	connection, port, macbook, broke, adapter
Cluster 6	camera_speaker_netflix_player_streaming	Media Devices & Camera Gear	speaker, camera, netflix, install, setup
Cluster 9	charge_charging_plug_cable_ipad	Charging Cables & Accessories	charge, charging, plug, cable, battery
Cluster 10	phone_button_heavy_control_tv	Remotes & Control Devices	remote, button, control, tv, device
Cluster 15	price_price good_good_key_case	Budget Tech & Durability	price, good, case, durability, battery

Table 1: Summary of Clusters with Assigned Labels and Key Terms

To assign meaningful labels to each cluster, we first examined the BERTopic-generated topic labels, which summarize the most representative keywords for each cluster. We then reviewed the top keywords and a sample of representative reviews to interpret the underlying themes. For example, Cluster 1 contained terms like customer, service, screen, plug, and support, suggesting a focus on Customer Support & Usability. Cluster 3 included connection, port, macbook, broke, and adapter, pointing to persistent issues with Computer Accessories & Ports. Cluster 6 centered on speaker, camera, netflix, install, and setup, reflecting experiences with Media Devices & Camera Gear. Cluster 9 featured keywords such as charge, charging, plug, cable, and battery, aligning with themes of Charging Cables & Accessories. In Cluster 10, terms like remote, button, control, tv, and device pointed to issues with Remotes & Control Devices, while Cluster 15 included price, good, durability, and battery, clearly related to Budget Tech & Durability.

With each cluster assigned to a product category or user experience theme, the analysis proceeded to trace how emotional expression evolved within and across these groupings. A series of visualizations and computational techniques were applied to quantify emotional trajectories, compare cluster-level sentiment profiles, and contextualize linguistic patterns over time.

The first visualization in the pipeline was a stacked bar chart showing the yearly composition of all ten NRC emotions across the full review corpus from 2010 to 2017. This chart provided a macroscopic view of overall emotional sentiment within the dataset. To examine variation across clusters, a radar plot was generated showing the average emotion composition per cluster, allowing for a direct comparison of sentiment dominance and emotional breadth.

Cluster prominence over time was then mapped using a line plot of cluster relevance, calculated as the percentage of total reviews per year assigned to each cluster label. This step ensured that any emotional shift could be interpreted in the context of how visible or relevant the topic was.

Emotion drift within each cluster was then visualized using individual line plots showing yearly percentages of each emotion category. These graphs were supported by numeric summary tables reporting both the raw yearly distributions and year-over-year percentage changes. This quantitative layer enabled identification of long-term erosion in sentiments like joy and trust, as well as short-term emotion spikes indicative of cluster-specific crises or product issues.

To complement the proportional emotion trends, a TF-IDF-based approach was used to extract the most distinctive emotion-specific words from each cluster across two representative periods: 2010–2013 and 2015–2017. Reviews were grouped by emotion and time window, and a TfidfVectorizer identified top terms per group, revealing how emotional expression evolved linguistically. This method helped capture the tone of user concerns, frustrations, and expectations over time and provided interpretive depth into shifts in emotion.

Results

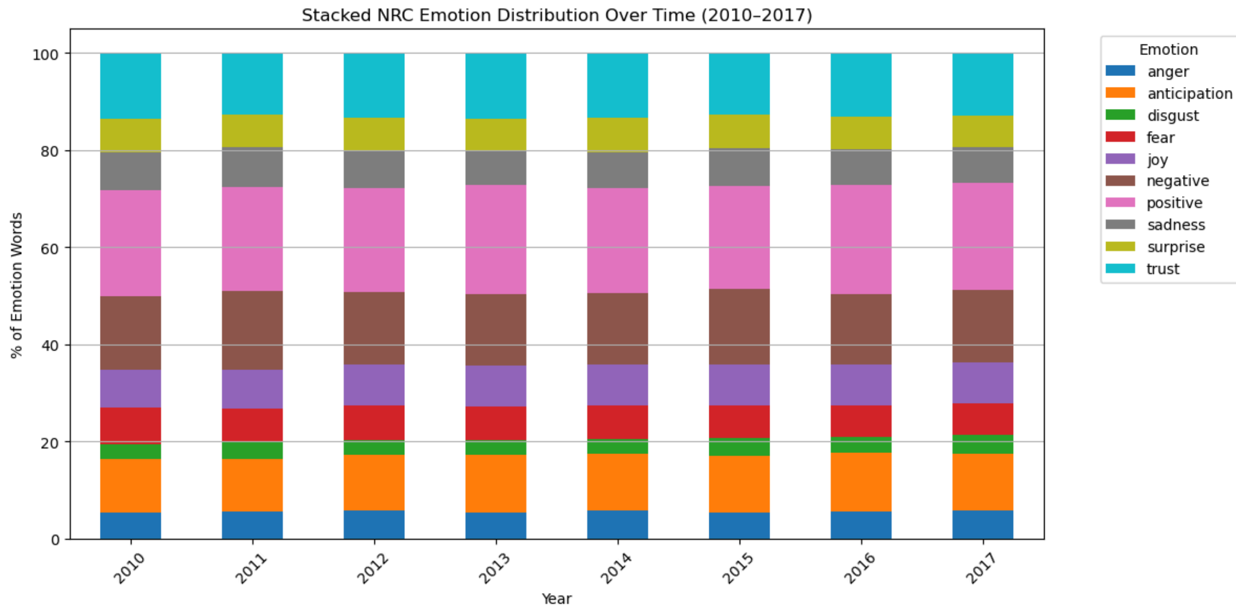

Figure 2: Stacked NRC Distribution Over Time

The stacked bar chart presents the percentage distribution of ten emotional categories—anger, anticipation, disgust, fear, joy, negative, positive, sadness, surprise, and trust—across an eight-year span. Each colored segment represents the proportion of words associated with that emotion in the corpus for a given year. What stands out most is the consistency in emotional distribution throughout the entire period. The colored bands are nearly identical from 2010 to 2017, indicating that sentiment within the corpus remained stable and did not undergo any noticeable shifts over time.

Positive emotions dominate the overall emotional tone. It occupies a larger proportion than any negative emotion and even outweighs the combined total of negative emotions, which include anger, fear, sadness, disgust, and the general "negative" category. In addition, emotions like joy, trust, and anticipation make up a significant portion, reinforcing the impression of optimism. Negative emotions maintain a relatively smaller and consistent presence. Notably, there are no sharp spikes in anger, fear, or disgust, typically associated with conflict or crisis.

Fear and sadness dip slightly during the 2011–2012 period, while trust and anticipation experience a mild increase. These small changes may reflect short term mood changes but are not substantial enough to suggest a structural change in sentiment. Emotions like surprise and disgust remain the least prevalent throughout the entire period, and their steady presence suggests they are not notable.

Overall, the chart reveals emotional stability and a predominantly positive tone from 2010 to 2017. Minor fluctuations in individual emotions, such as a gentle rise in anticipation and trust, point to a slightly more hopeful future. However, the lack of change in negative emotions suggests either a consistently positive response, or the use of filters to remove controversial content.

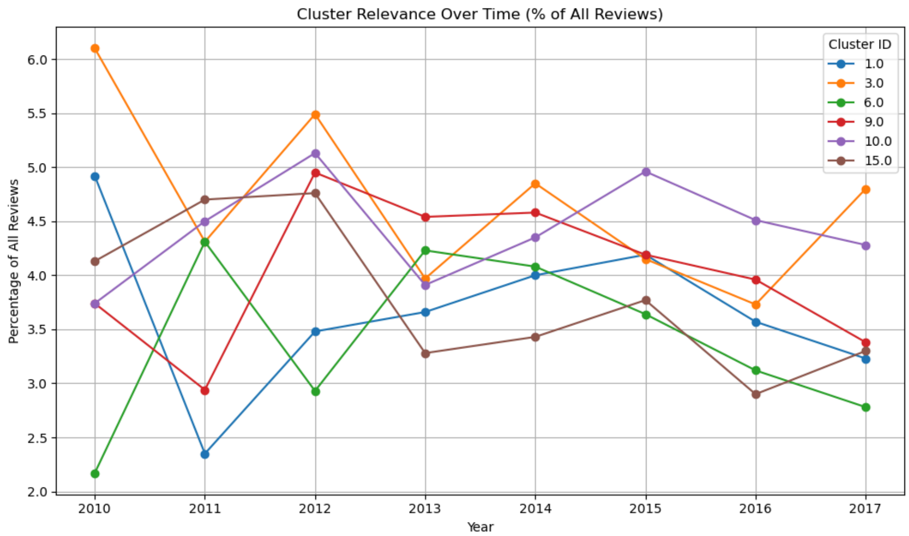

Figure 3: Cluster Relevance Over Time

The emotion profiles of the clusters are all similar, indicating that emotional tone is not a major cause of cluster differentiation. The lines for all six clusters largely overlap, suggesting similar proportions of each emotion. The positive and negative categories dominate the plot with averages around 0.15 - 0.20, which is consistent with the stacked bar chart. These two categories are much higher than other emotions like disgust, fear, or anger. Cluster 3 shows a slightly higher level of anticipation and anger than the others though the differences are small (~0.01–0.02). Surprise, trust, disgust, and fear remain low and consistent, around 0.05 or below, showing little variation across clusters. Disgust and fear, in particular, are the least prominent emotions. The clusters differ only slightly in emotional tone, with most sharing a common emotional structure.

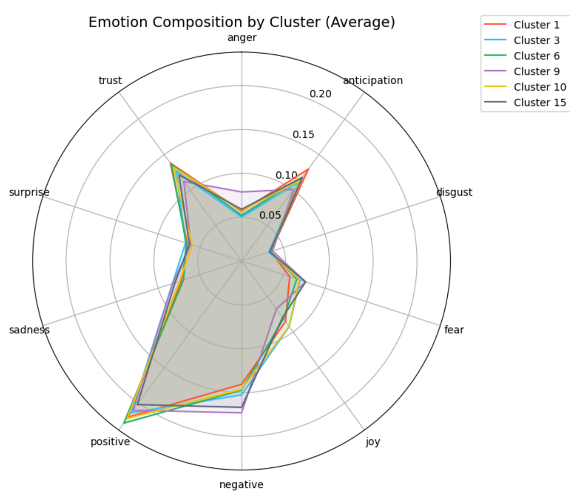

Figure 4: Radar Plot

Each cluster stays within a narrow range (2–6%) indicating a diverse set of topics/emotional tones in the reviews, no single theme overpowered one another.

2012–2014 shows the greatest change, where there were up and down shifts across multiple clusters suggesting this was a period of dynamic change. Clusters 3 and 10 both maintain high relevance throughout most of the timeline, suggesting that their underlying themes remained consistently important across different periods. Cluster 6. shows a steady decline in prominence post-2014 which supports the idea that product, rather than emotion, is the driving factor behind the evolution and shifts of each cluster over time. The emotional tone is relatively stable across all clusters, with subtle variations, with some clusters rising or declining in importance depending on the year.

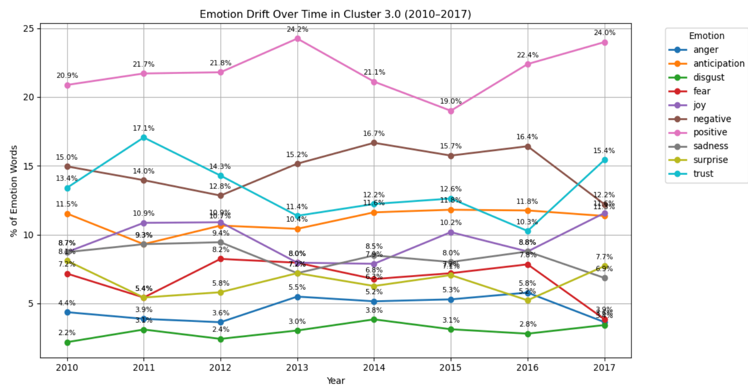

Figure 5: Emotion Drift Over Time – Computer Accessories & Ports (Cluster 3)

Top NRC Emotion Words (TF-IDF) — Cluster 3

Emotion	2010–2013 Top Words	2015–2017 Top Words
Anger	money, noisy, battery, bad, blast, annoying	battery, bad, money, stolen, noisy, worthless
Anticipation	time, good, star, store, money, watch	good, time, thought, long, star, pretty
Disgust	larger, bad, shoddy, defective, powerful, disappointed	bad, waste, defective, worthless, rubbish, weight
Fear	case, problem, watch, bad, blast, avoid	case, problem, bad, broke, change, broken
Joy	good, star, money, green, found, love	good, star, happy, pretty, gift, money
Sadness	case, blue, problem, bad, dark, disappointing	case, problem, bad, disconnect, broke, lost
Surprise	good, cable, money, guess, larger, gift	good, gift, money, cable, randomly, sun
Trust	good, star, durable, recommend, money, shoulder	good, cover, star, pretty, happy, money
Positive	good, worth, sturdy, star, store, durable	good, sturdy, star, decent, brightness, gift
Negative	case, small, problem, cheap, flap, wrong	case, battery, problem, small, cheap, noise

Table 2: Top NRC Emotion Words (TF-IDF) by Emotion Category for Computer Accessories & Ports (Cluster 3) Across Two Periods (2010–2013 vs. 2015–2017)

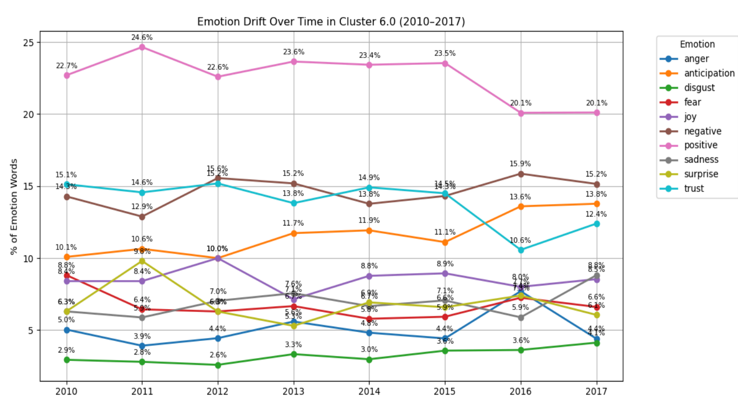

Figure 6: Emotion Drift Over Time – Media Devices & Camera Gear (Cluster 6)

Top NRC Emotion Words (TF–IDF) — Cluster 6

Emotion	2010–2013 Top Words	2015–2017 Top Words
Anger	battery, rebel, complaint, bad, shoot, tighten	battery, bad, disappointed, complaint, pound, money
Anticipation	good, time, top, pretty, install, network	good, time, install, top, pretty, star
Disgust	larger, interior, bad, disappointed, weight, hood	bad, disappointed, larger, weight, hanging, ridiculous
Fear	case, problem, change, rebel, bad, shoot	case, problem, bad, change, shoot, shooting
Joy	good, pretty, star, pay, perfect, happy	good, pretty, star, love, perfect, excellent
Sadness	case, problem, bottom, fall, bad, lost	case, problem, bad, disappointed, lower, bottom
Surprise	good, cable, larger, trip, jolt, deal	good, cable, money, larger, weight, catch
Trust	good, system, top, recommend, cover, shoulder	good, top, budget, pretty, star, real
Positive	good, extra, top, recommend, gear, padding	good, top, worth, pretty, received, star
Negative	case, small, problem, battery, player, cheap	small, case, problem, battery, cheap, bad

Table 3: Top NRC Emotion Words (TF-IDF) by Emotion Category for Media Devices & Camera Gear (Cluster 6) Across Two Periods (2010–2013 vs. 2015–2017)

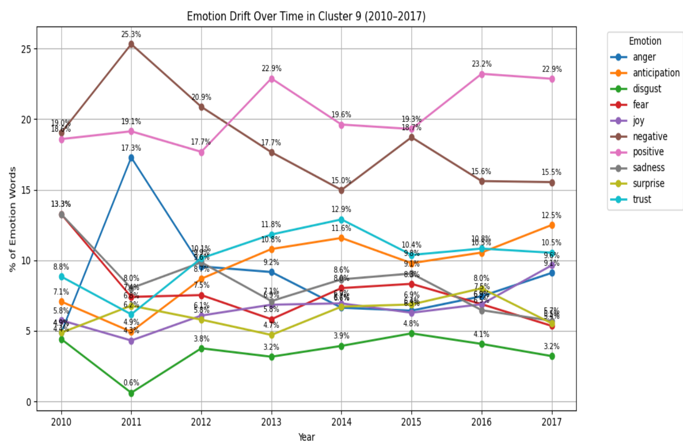

Figure 7: Emotion Drift Over Time – Charging Cables & Accessories (Cluster 9)

Top NRC Emotion Words (TF–IDF) — Cluster 9

Emotion	2010–2013 Top Words	2015–2017 Top Words
Anger	battery, elbow, disappointed, hit, money, damage	battery, smell, bad, broken, disappointed, hot
Anticipation	time, long, good, expected, star, start	time, good, long, expected, star, happy
Disgust	disappointed, damage, defective, nose, feeling, bad	smell, bad, disappointed, failure, terrible, powerful
Fear	case, difficult, problem, broke, feeling, bad	case, problem, difficult, bad, broken, failure
Joy	good, star, found, daughter, perfect, kind	good, star, pleased, found, excellent, happy
Sadness	case, problem, lower, dark, disappointed, lost	case, problem, bad, broken, disappointed, lost
Surprise	cable, good, guess, slip, money, feeling	cable, good, break, chance, trip, guess
Trust	good, microscope, star, cover, found, fully	good, recommend, warranty, star, show, found
Positive	charger, focus, good, degree, received, working	working, charger, good, reader, recommend, full
Negative	battery, case, small, cheap, problem, lower	battery, case, problem, cheap, wrong, smell

Table 4: Top NRC Emotion Words (TF-IDF) by Emotion Category for Charging Cables & Accessories (Cluster 9) Across Two Periods (2010–2013 vs. 2015–2017)

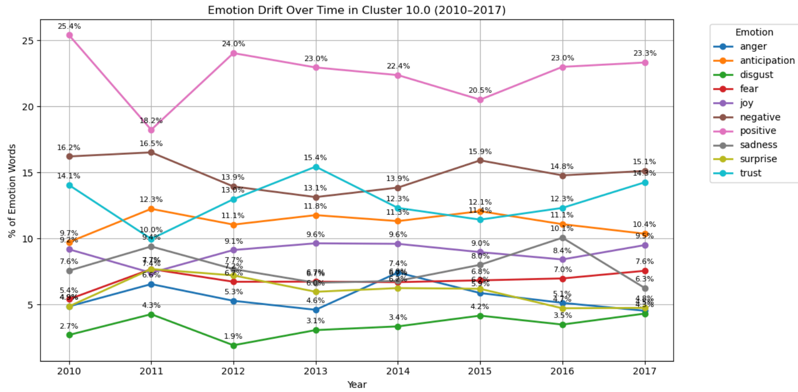

Figure 8: Emotion Drift Over Time – Remotes & Control Devices (Cluster 10)

Top NRC Emotion Words (TF-IDF) – Cluster 10

Emotion	2010–2013 Top Words	2015–2017 Top Words
Anger	battery, bad, limited, complaint, wireless, hate	battery, annoying, bad, smell, tighten, disappointed
Anticipation	good, time, long, buddy, start, daily	time, good, long, thought, star, pretty
Disgust	bad, hate, larger, weird, unnatural, garbage	bad, crap, smell, finally, defective, weight
Fear	problem, difficult, bad, pain, broke, watch	problem, change, case, bad, watch, fire
Joy	good, harmony, buddy, love, pay, star	good, love, star, pretty, harmony, excellent
Sadness	problem, bad, pain, broke, limited, ultimate	problem, lower, case, dark, bad, flaw
Surprise	good, cable, break, guess, wireless, surprised	good, cable, break, finally, hope, deal
Trust	good, harmony, fixed, buddy, recommend, system	good, instruction, star, manual, pretty, system
Positive	good, feature, harmony, option, working, model	good, working, model, instruction, extra, job
Negative	problem, battery, small, cheap, bad, wrong	problem, battery, small, annoying, lower, cheap

Table 5: Top NRC Emotion Words (TF-IDF) by Emotion Category for Remotes & Control Devices (Cluster 10) Across Two Periods (2010–2013 vs. 2015–2017)

The emotion drift analysis for Clusters 3, 6, 9, and 10 over the 2010–2017 period reveals both emotional patterns and notable deviations across clusters. The most consistent emotion is the dominance of "positive" emotions across all four clusters. This emotion category consistently remains the most frequently used, hovering between 20% and 25% of all emotion-related words each year.

For example, in Cluster 3, positivity peaks at 24.8% in 2017, indicating a rise in affirming or constructive discourse toward the end of the observed period. It shows a strong and steadily increasing dominance of positive sentiment over time. Starting around 20% in 2010, indicating a long-term rise in affirming or satisfactory customer experience This upward trend could reflect increasing user satisfaction, consistent product improvement, or stronger community engagement. This is also supported by the stable levels of joy and trust, which, while not as dominant, show mild fluctuations—trust, for example, ranges from around 10–13%, showing moderate confidence in the product associated with this cluster. Anticipation remains relatively stable throughout the years, suggesting steady interest or engagement with future-oriented topics. Negative emotions such as anger and sadness are consistently low, and there are no noticeable spikes, indicating an emotionally steady environment with little conflict or disappointment. This cluster likely represents content that matured positively over time or consistently met user expectations.

Similarly, Cluster 10 demonstrates the most emotionally balanced timeline. Positive sentiment is consistently dominant, with high values of 25.4% in 2010 and 24.8% in 2012, and it remains steady through 2017. Its strong positivity and its other associated emotions such as joy, anticipation, and trust, all maintain consistent levels throughout the years. Joy, for example, remains above 10% in most years, and trust stays steady around 11–13%, suggesting a harmonious blend of emotional experiences. Negative emotions are notably low and stable; anger, sadness, disgust, and surprise, reflecting a stable and satisfied environment with minimal emotional disruption. The even distribution of emotions implies that Cluster 10 could represent an established product, service, or community with a loyal user base and few fluctuations in user experience.

In contrast, emotions such as joy and trust, though also positive, exhibit more varied and moderate levels across time. These emotions often range between 5% and 15%, showing year-to-year shifts and not consistently dominating any cluster. For instance, in Cluster 6, trust reached a notable peak of 15.8% in 2012, suggesting a temporary rise in confidence or assurance potentially tying to a product improvement or positive news during that year. However, trust steadily declines afterward, leveling out to 12.4% by 2017. Similarly, joy in Cluster 10 remains relatively stable around the 10–12% mark but never surpasses the general positivity rate. This contrast shows that although overall positive sentiment is prevalent, particular emotions like happiness and trust tend to vary more, likely influenced by specific events, announcements, or shifts in user experience.

Each cluster displays some unique emotional dynamics. Cluster 6, maintains relatively high levels of trust and anticipation, with trust peaking at 15.8% in 2012. Anticipation is generally above 10%, indicating that users in this cluster were actively looking forward to developments or updates. The strong sense of reliability or loyalty during that year possibly due to a successful product rollout, positive community feedback, or a path to future improvements. Positive sentiment remains strong throughout, peaking in 2015 and maintaining above 20% in most years, reinforcing the sense of a well established product or good customer service. Negative emotions remain consistently low with anger, disgust, and sadness never showing major fluctuations suggesting a calm, trusted environment. This emotional makeup implies that Cluster 6 may be associated with reliability, continually evolving upwards and maintaining community confidence over the years.

Cluster 9 is the most emotionally unstable of the four. The most obvious change is a dramatic spike in both anger and negative sentiment in 2011, with anger reaching 17.7% and negative peaking at 25.3%, far exceeding levels seen in any other cluster or year. This major change in reaction suggests that something specific such as a controversial change or product failure had triggered the widespread dissatisfaction or backlash among users. Following this spike, negative emotions quickly decline, suggesting that the event was temporary, though impactful. Interestingly, positive sentiment still remains present and recovers in later years, indicating that while the 2011 event caused disruption, the general sentiment trend eventually returned to a more neutral or positive outcome. Trust, joy, and anticipation fluctuate post-2011, but they never fully dominate. This cluster likely represents a product or community that underwent a crisis or major change and then gradually regained balance.

TF-IDF provides a deeper understanding of how emotional tone and content evolve across clusters from 2010 to 2017. While emotion scores reveal consistent positive sentiment—particularly in Clusters 3, 6, and 10, TF-IDF highlights the specific terms driving these emotional trends. For instance, rising positivity in Cluster 3 aligns with high-weighted terms like “worth” or “sturdy,” while peaks in trust and anticipation in Cluster 6 during 2012 may be linked to keywords such as “time” or “recommend.” In contrast, Cluster 9’s spike in negative emotions in 2011 is likely associated with event-specific terms like “problem” or “limited,” suggesting a controversy or product failure

Across all four clusters, emotions such as surprise, disgust, and sadness stay consistently low, usually remaining below 5%. This lack of strong negative sentiment supports how emotional tone across the dataset was largely steady, and not frequently driven by emotionally extreme events. The stability of these emotions also helps to emphasize the positivity and its emotional counterparts: anticipation, trust, and joy as the core affective components shaping user discourse over the 2010–2017 period.

The emotion drift patterns highlight both consistency and diversity in emotional expression across clusters. While all clusters exhibit a strong foundation in positive sentiment, likely tied to contentment or loyalty, the presence of distinct emotional shifts such as anger and negativity in Cluster 9 or anticipation and trust in Cluster 6.0 reflect the influence of specific topics, events, or user experiences. The sustained optimism combined with varied emotional textures suggests that while the overarching tone is affirming, each cluster reflects its own emotional identity shaped by community dynamics, external developments, and evolving user expectations.

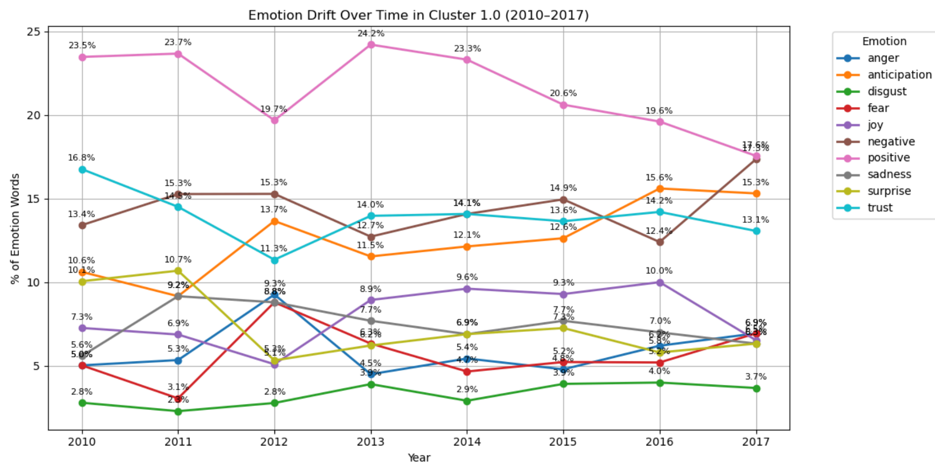

Figure 5: Emotion Drift Over Time – Customer Support & Usability (Cluster 1)

Top NRC Emotion Words (TF-IDF) – Cluster 1

Emotion	2010–2013 Top Words	2015–2017 Top Words
Anger	bad, rating, battery, money, ram, retract	ram, money, battery, bad, hot, annoying
Anticipation	board, time, good, install, long, money	time, board, good, ram, long, money
Disgust	bad, waste, default, damage, terrible, defective	waste, bad, terrible, lemon, damn, wasting
Fear	bad, problem, rating, case, change, watch	problem, case, bad, difficult, spike, terrible
Joy	good, found, love, money, star, music	good, money, love, star, pretty, kind
Sadness	strip, bad, problem, rating, error, music	strip, problem, case, bad, flaw, unacceptable
Surprise	surge, good, cable, money, present, accidentally	surge, good, money, surprised, cable, guess
Trust	good, protector, show, manual, system, recommend	good, protector, system, money, pretty, star
Positive	good, customer, feature, protector, focus, build	good, protector, money, love, working, received
Negative	strip, bad, problem, waste, rating, small	waste, ram, cheap, copy, strip, small

Table 6: Top NRC Emotion Words (TF-IDF) by Emotion Category for Customer Support & Usability (Cluster 1) Across Two Periods (2010–2013 vs. 2015–2017)

Cluster 1 captures reviews primarily concerned with product functionality and the quality of customer support. In 2010, emotional tone was strongly positive, with positive sentiment comprising 23.46% of emotion words, followed by trust with 16.76%, together exceeding 40%. These figures reflected a high satisfaction, with reviewers praising product reliability, ease of use, and support systems. At the same time, negative emotions remained steady as anger was 5.03%, disgust 2.79%, and fear 5.03%, suggesting only isolated cases of dissatisfaction.

However, by 2012, this emotional landscape began to shift. Trust dropped steeply to 11.34% a 5.42-point decline from 2010, and positive sentiment fell to 19.68%. Meanwhile, anticipation jumped to 13.66%, and anger surged to a peak of 9.26%, nearly doubling from two years prior. Fear also increased significantly to 8.80%. These rises indicate mounting frustrations with either support reliability or product breakdowns. This was further reflected in the 2012 year-over-year change: anger rose by 3.92%, and fear by 5.75%, while positive sentiment dropped by 3.98%.

From 2013 to 2015, emotional trends were unstable. Although joy peaked in 2014 at 9.61%, and trust briefly recovered to 14.08%, these gains were short-lived. By 2015, positive sentiment dropped again to 20.61%, and trust declined to 13.64%. Anticipation stayed high at 12.63%, reinforcing a continued shift toward expectations rather than contentment. While, negative sentiment reached 14.95%, and anger held at 4.79%. These shifts suggest that although satisfaction persisted for some, broader uncertainty and concern began to shape the cluster's emotional tone more dominantly.

By 2017, this shift was unmistakable. Anticipation rose to its highest level of 15.31%, becoming the dominant emotion in the cluster. Trust had fallen to 13.06%, and positive sentiment reached its lowest point of the series at 17.55%, a 5.91% drop from 2010. In contrast, negative sentiment hit its peak at 17.35%, up nearly 4% from the start of the decade. Anger and fear both settled at 6.94%, marking elevated baselines compared to early years. Overall, emotions signaling dissatisfaction, concern, and anticipation clearly overtook those of trust and joy.

TF-IDF word trends support this emotional transformation. In the early years (2010–2013), high-ranking emotion words included “good,” “customer,” “manual,” “feature,” “recommend,” and “build” suggesting reliability, satisfaction, and functional design. By contrast, in 2015–2017, terms like “ram,” “cheap,” “copy,” “problem,” “waste,” and “working” became more prevalent across anger, anticipation, and negative categories. This lexical shift from affirming to problem-oriented reflects the erosion of confidence in both products and support infrastructure.

Taken together, the emotional arc of Cluster 1 reflects a transition from confident satisfaction to frustrated expectation. Over eight years, core emotions like trust and positivity steadily declined, while anticipation, negative sentiment, and anger rose sharply. This suggests that users increasingly experienced unresolved issues or deteriorating service, prompting a shift from celebrating what worked to hoping for improvement.

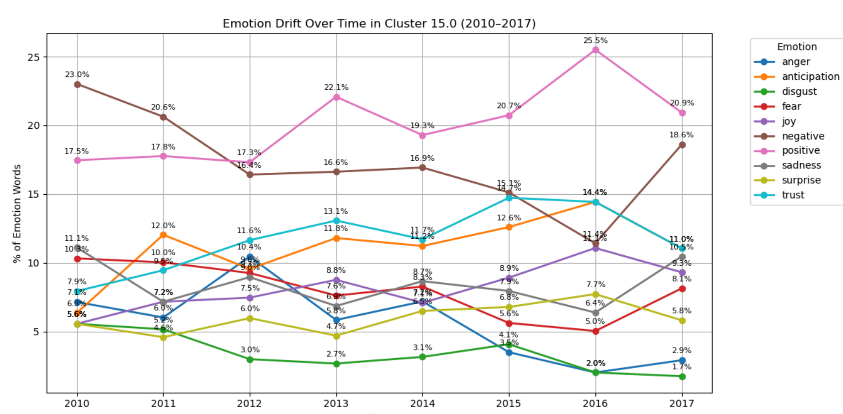

Figure 10: Emotion Drift Over Time – Budget Tech & Durability (Cluster 15)

Top NRC Emotion Words (TF-IDF) — Cluster 15

Emotion	2010–2013 Top Words	2015–2017 Top Words
Anger	battery, hot, bad, hit, remove, broken	delay, bad, money, disappointed, complain, battery
Anticipation	time, good, pretty, star, start, long	good, time, result, long, store, expected
Disgust	bad, failure, waste, crap, defective, weird	delay, bad, disappointed, trash, waste, finally
Fear	problem, fire, case, bad, remove, broken	problem, case, broke, delay, bad, fire
Joy	good, pretty, star, found, money, perfect	good, love, excellent, happy, deal, found
Sadness	problem, case, bad, remove, broken, shot	problem, case, bottom, broke, delay, bad
Surprise	good, money, pop, shot, fluke, luck	good, guess, deal, money, finally, expect
Trust	good, pretty, star, found, manual, machine	good, cover, manual, excellent, happy, school
Positive	good, completely, working, pretty, model, star	good, focus, slim, working, store, love
Negative	player, problem, small, battery, case, eject	player, problem, cheap, case, copy, bottom

Table 7: Top NRC Emotion Words (TF-IDF) by Emotion Category for Cluster 15 Across Two Periods (2010–2013 vs. 2015–2017)

Cluster 15 reflects user sentiment around affordable electronics, particularly tradeoffs between price and durability. In 2010, the emotional tone was predominantly negative where negative sentiment led at 23.02%, followed by positive at 17.46% and trust at 7.94%. Fear 10.32%, anger 7.14%, and sadness 11.11% were also notably high, indicating early concerns around longevity and reliability. These reviews often conveyed frustration or resignation despite low price points.

By 2012, the emotional landscape began to shift. Trust rose to 11.64%, a 3.70-point increase, and anticipation climbed to 9.55%, reflecting rising hope for performance improvements. Joy also increased to 7.46%, while anger peaked at 10.45%, up over 3 points from 2010. These trends suggest a growing mix of optimism and frustration, as expectations evolved alongside recurring issues.

From 2013 to 2015, emotional tone became more balanced. Positive sentiment peaked at 22.08% in 2013, and trust reached 14.73% by 2015. Anticipation rose to 12.60%, while anger and disgust dropped to 3.49% and 4.07%, respectively. Joy remained strong, with users increasingly emphasizing functional value. TF-IDF words such as “love,” “deal,” “slim,” and “working” reflected a temporary rise in satisfaction and perceived utility.

2016 marked the emotional high point. Positive sentiment reached 25.50%, joy climbed to 11.07%, and anticipation hit 14.43%, the cluster’s peak. Meanwhile, anger and disgust dropped to just 2.01% each, indicating minimal severe criticism. However, this optimism didn’t last.

By 2017, sentiment turned more mixed. Positive sentiment dropped to 20.93%, and trust fell to 11.05%. Negative sentiment surged to 18.60%, a 7.19% increase from 2016. Sadness rose to 10.47%, and fear to 8.14%, while anticipation dipped to 11.05%. The shift of negative emotions suggests resurfacing concerns about product quality.

TF-IDF patterns reinforce this trajectory. Early terms included “remove,” “broken,” “model,” and “failure,” highlighting reliability issues. From 2015 onward, negative terms like “delay,” “disappointed,” “trash,” and “broke” became prominent, though positive words like “excellent” and “happy” remained. This mix reflects continued appreciation for value but increasing frustration with tradeoffs.

Overall, Cluster 15 traces an arc from early dissatisfaction to mid-decade optimism, followed by renewed skepticism. While users embraced affordability, recurring concerns about reliability led to a tempered emotional tone with less outrage, but more resignation and guarded hope.

Discussion

The results show that emotional tone in Amazon electronics reviews remained largely consistent from 2010 to 2017, with positive emotions dominating across all years and clusters. This stability suggests that, despite the shift from the platform's early adoption phase to its period of widespread use, users maintained a generally optimistic tone in their reviews. Positive sentiment, including trust, anticipation, and joy, consistently outweighed negative emotions like anger, fear, and sadness. This finding confirms the expectation that emotional tone would be relatively steady, reflecting a maturing platform where users gradually built familiarity and trust with products and the reviewing process.

Our results suggest new insights where the overall emotional distribution remained similar across all years, individual clusters representing different product categories display subtle emotional shifts that indicate changing user expectations or specific product dynamics. For example, in some clusters, we observed a gradual increase in positive sentiment, which may reflect improvements in product quality, design, or user satisfaction over time. In contrast, other clusters showed slight declines in trust or anticipation, possibly indicating unmet expectations, reduced innovation, or shifting consumer interest. These patterns suggest that while the broader emotional tone across the platform appears stable, the experiences within specific product categories are more dynamic. Users may react to updates, faultiness, customer service, or external factors which can all influence the emotional tone captured in their reviews. These small changes show why it is important to not just look at the overall emotions, but also within specific product categories. Doing so helps us better understand how customer's feelings change over time and what specific factors such as product issues or improvements might be influencing them.

For example, Cluster 3 shows an upward trend in positivity over time, suggesting improved user satisfaction or product refinement while Cluster 6 displays a peak in trust followed by a slight decline, hinting at possible decrease of confidence in that product area. Most notably, Cluster 9 experienced a temporary spike in anger and negativity in 2011, likely linked to a specific product issue or external event. These examples demonstrate that while the platform's overall emotional tone was positive and stable, emotional fluctuations did occur and were often short term. This adds nuance to our understanding of emotional tone by showing that consistency can mask smaller emotional deviations within specific themes or products.

Tying this back to the main research question, the results suggest that emotional tone does not vary dramatically between the early adoption and widespread use phases in a broad sense. However, within individual product categories, some emotional drift is evident, suggesting that emotional patterns are not entirely uniform across thematic groupings. The consistent dominance of positivity suggests that different product categories share a similar emotional tone, likely influenced by how people write reviews on the platform, what users expect, and how electronics generally work as reliable, functional items. However, we can see that the emotional dynamics of individual clusters reveal that product-specific factors such as failures or community feedback play a key role in shaping tone over time.

These findings contribute to our broader understanding of how emotional expression evolves in digital consumer feedback. They show that while emotional stability is common in large-scale review datasets, important shifts can still occur within subgroups, especially in response to product-specific developments. The Amazon electronics reviews from 2010–2017 show patterns of steady positivity, occasional spikes in negativity, and category-specific drift that may apply to other platforms and product types. Our findings help clarify not only how emotional tone varies across categories and time periods, but also how emotional patterns are shaped by the interaction between platform dynamics and user experience.

In conclusion, our analysis highlights a stable and predominantly positive emotional tone in

Amazon electronics reviews from 2010 to 2017, with minor deviations. While the broader sentiment remained consistent throughout both the early adoption and widespread use phases of the platform, the subtle emotional shifts within specific clusters reveal how user experiences, product developments, and community reactions can influence sentiment in certain ways. These findings show that while the overall emotional tone stays relatively similar, deeper analysis reveals changes influenced by how people react to specific products. This helps answer our research question and shows why it’s important to look at both the overall trends and small differences when analyzing customer reviews. It gives a clearer view of how people express emotions online and can help businesses, researchers, and designers better understand how users feel and stay engaged over time.

Limitations and Future Work

A key limitation of the study lies in the scope and structure of the dataset. Since the analysis focused solely on Amazon electronics reviews, the findings may not extend to other product categories where customer expectations and emotional expressions differ. Reviews from 2000 to 2009 were excluded due to extreme sparsity, and data from 2018 was not included because the year was incomplete. As a result, the analysis may overlook important early sentiment patterns or more recent shifts. Furthermore, the dataset didn’t contain any reviews beyond 2018, preventing examination of consumer sentiment during a period marked by rapid technological change. The rise of AI-driven products and smart home technologies between 2019 and 2025 may have significantly reshaped user expectations and emotional responses.

In terms of methodology, the use of the NRC Emotion Lexicon, while valuable for categorizing emotions, doesn't account for context, sarcasm, which can lead to misclassification of sentiment in more nuanced reviews. Future analysis could incorporate context aware sentiment tools and other tools such as VADER or TextBlob to generate sentence or review level sentiment scores that reflect polarity and intensity more effectively. Combining these tools with NRC could have potentially offered a more robust representation of emotional tone, especially for informal or conversational language found in reviews.

The analysis could be further expanded through the application of supervised learning techniques, such as logistic regression or random forest models, to classify emotional sentiment or to validate and refine the existing unsupervised clusters. Incorporating numeric star ratings into the analysis would allow for comparisons between predicted sentiment and assigned ratings, potentially revealing discrepancies such as reviews that express frustration despite high ratings or unexpectedly positive language in lowly rated reviews. Additional depth could also be achieved by predicting review helpfulness, or segmenting users based on review behavior, enabling a more comprehensive understanding of how emotional expression varies across different user groups over time.

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A Appendix

Cluster Relevance (% of All Reviews Per Year):

	Year	1	3	6	9	10	15
0	2010	4.92	6.1	2.17	3.74	3.74	4.13
1	2011	2.35	4.31	4.31	2.94	4.5	4.7
2	2012	3.48	5.49	2.93	4.95	5.13	4.76
3	2013	3.66	3.97	4.23	4.54	3.91	3.28
4	2014	4	4.85	4.08	4.58	4.35	3.43
5	2015	4.19	4.15	3.64	4.19	4.96	3.77
6	2016	3.57	3.73	3.12	3.96	4.51	2.9
7	2017	3.23	4.8	2.78	3.38	4.28	3.3

Table A1: Cluster Relevance by Year (% of All Reviews, 2010–2017)

Year-over-Year Percent Change in Cluster Relevance:

	Year	1	3	6	9	10	15
0	2010	0	0	0	0	0	0
1	2011	-52.24	-29.34	98.62	-21.39	20.32	13.8
2	2012	48.09	27.38	-32.02	68.37	14	1.28
3	2013	5.17	-27.69	44.37	-8.28	-23.78	-31.09
4	2014	9.29	22.17	-3.55	0.88	11.25	4.57
5	2015	4.75	-14.43	-10.78	-8.52	14.02	9.91
6	2016	-14.8	-10.12	-14.29	-5.49	-9.07	-23.08
7	2017	-9.52	28.69	-10.9	-14.65	-5.1	13.79

Table A2: Year-over-Year Percent Change in Cluster Relevance (2010–2017)

=== Peak Emotion Years by Cluster ===

	anger	anticipation	disgust	fear	joy	negative	positive	sadness	surprise	trust
1	2012	2016	2016	2012	2016	2017	2013	2011	2011	2010
3	2016	2015	2014	2012	2017	2014	2013	2012	2010	2011
6	2016	2017	2017	2010	2012	2016	2011	2017	2011	2012
9	2011	2017	2015	2010	2017	2011	2016	2010	2016	2014
10	2014	2011	2017	2011	2013	2011	2010	2016	2011	2013
15	2012	2016	2010	2010	2016	2010	2016	2010	2016	2015

Table A3: Peak Emotion Expression Year per Cluster by Emotion Category

=== Percent Change in Emotion Use (2010 to Last Year) ===

	anger	anticipation	disgust	fear	joy	negative	positive	sadness	surprise	trust
1	38	44.2	31.51	38	-10.08	29.38	-25.2	13.24	-37.09	-22.07
3	-16.53	-1.54	57.11	-46.21	32.56	-18.38	14.9	-21.44	-4.83	15.09
6	-12.58	36.59	40.5	-25.07	1.63	6.06	-11.37	39.87	-3.84	-18.04
9	87.11	76.56	-27.36	-59.64	67.64	-18.35	22.99	-56.95	13.73	19.05
10	-6.77	6.55	59.83	39.85	3.42	-6.77	-8.18	-17.23	-2.33	1.43
15	-59.3	73.98	-68.6	-21.11	67.44	-19.17	19.87	-5.81	4.65	39.19

Table A4: Percent Change in Emotion Use from 2010 to 2017

=== Yearly Dominant Emotions by Cluster ===

	2010	2011	2012	2013	2014	2015	2016	2017
1	trust	trust	anticipation	trust	trust	trust	anticipation	anticipation
3	trust	trust	trust	trust	trust	trust	anticipation	trust
6	trust	trust	trust	trust	trust	trust	anticipation	anticipation
9	fear	anger	trust	trust	trust	trust	trust	anticipation
10	trust	anticipation	trust	trust	trust	anticipation	trust	trust
15	sadness	anticipation	trust	trust	trust	trust	anticipation	anticipation

Table A5: Dominant Emotion by Cluster and Year (2010–2017)

Emotion Distribution (%) — Cluster 1.0

	year	anger	anticipation	disgust	fear	joy	negative	positive	sadness	surprise	trust
0	2010.00	5.03	10.61	2.79	5.03	7.26	13.41	23.46	5.59	10.06	16.76
1	2011.00	5.34	9.16	2.29	3.05	6.87	15.27	23.66	9.16	10.69	14.50
2	2012.00	9.26	13.66	2.78	8.80	5.09	15.28	19.68	8.80	5.32	11.34
3	2013.00	4.50	11.54	3.91	6.33	8.93	12.72	24.20	7.69	6.21	13.96
4	2014.00	5.44	12.14	2.91	4.66	9.61	14.08	23.30	6.89	6.89	14.08
5	2015.00	4.79	12.63	3.92	5.22	9.29	14.95	20.61	7.69	7.26	13.64
6	2016.00	6.20	15.60	4.00	5.20	10.00	12.40	19.60	7.00	5.80	14.20
7	2017.00	6.94	15.31	3.67	6.94	6.53	17.35	17.55	6.33	6.33	13.06

Table A6: Emotion Distribution (%) by Year – Customer Support & Usability (Cluster 1)

Year—over—Year % Change — Cluster 1.0

	year	anger	anticipation	disgust	fear	joy	negative	positive	sadness	surprise	trust
0	2010	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
1	2011	0.31	−1.45	−0.5	−1.98	−0.39	1.86	0.2	3.57	0.63	−2.26
2	2012	3.92	4.5	0.49	5.75	−1.78	0.01	−3.98	−0.36	−5.37	−3.16
3	2013	−4.76	−2.12	1.13	−2.47	3.84	−2.56	4.52	−1.11	0.89	2.62
4	2014	0.94	0.6	−1.0	−1.67	0.68	1.36	−0.9	−0.8	0.68	0.12
5	2015	−0.65	0.49	1.01	0.56	−0.32	0.87	−2.69	0.8	0.37	−0.44
6	2016	1.41	2.97	0.08	−0.02	0.71	−2.55	−1.01	−0.69	−1.46	0.56
7	2017	0.74	−0.29	−0.33	1.74	−3.47	4.95	−2.05	−0.67	0.53	−1.14

Table A7: Year-over-Year Change in Emotion Distribution (%) – Customer Support & Usability (Cluster 1)

Emotion Distribution (%) — Cluster 3.0

	year	anger	anticipation	disgust	fear	joy	negative	positive	sadness	surprise	trust
0	2010.00	4.36	11.53	2.18	7.17	8.72	14.95	20.87	8.72	8.10	13.40
1	2011.00	3.88	9.30	3.10	5.43	10.85	13.95	21.71	9.30	5.43	17.05
2	2012.00	3.63	10.65	2.42	8.23	10.90	12.83	21.79	9.44	5.81	14.29
3	2013.00	5.49	10.42	3.03	7.95	7.95	15.15	24.24	7.20	7.20	11.36
4	2014.00	5.15	11.62	3.84	6.77	7.88	16.67	21.11	8.48	6.26	12.22
5	2015.00	5.29	11.80	3.12	7.19	10.18	15.74	19.00	8.01	7.06	12.62
6	2016.00	5.78	11.75	2.80	7.84	8.77	16.42	22.39	8.77	5.22	10.26
7	2017.00	3.64	11.35	3.43	3.85	11.56	12.21	23.98	6.85	7.71	15.42

Table A8: Emotion Distribution (%) by Year – Computer Accessories & Ports (Cluster 3)

Year-over-Year % Change — Cluster 3.0

	year	anger	anticipation	disgust	fear	joy	negative	positive	sadness	surprise	trust
0	2010	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
1	2011	−0.48	−2.23	0.92	−1.74	2.13	−1.0	0.84	0.58	−2.67	3.65
2	2012	−0.25	1.35	−0.68	2.8	0.05	−1.12	0.08	0.14	0.38	−2.76
3	2013	1.86	−0.23	0.61	−0.28	−2.95	2.32	2.45	−2.24	1.39	−2.93
4	2014	−0.34	1.2	0.81	−1.18	−0.07	1.52	−3.13	1.28	−0.94	0.86
5	2015	0.14	0.18	−0.72	0.42	2.3	−0.93	−2.11	−0.47	0.8	0.4
6	2016	0.49	−0.05	−0.32	0.65	−1.41	0.68	3.39	0.76	−1.84	−2.36
7	2017	−2.14	−0.4	0.63	−3.99	2.79	−4.21	1.59	−1.92	2.49	5.16

Table A9: Year-over-Year Change in Emotion Distribution (%) – Computer Accessories & Ports (Cluster 3)

Emotion Distribution (%) — Cluster 6.0

	year	anger	anticipation	disgust	fear	joy	negative	positive	sadness	surprise	trust
0	2010.00	5.04	10.08	2.94	8.82	8.40	14.29	22.69	6.30	6.30	15.13
1	2011.00	3.92	10.64	2.80	6.44	8.40	12.89	24.65	5.88	9.80	14.57
2	2012.00	4.44	10.00	2.59	6.30	10.00	15.56	22.59	7.04	6.30	15.19
3	2013.00	5.60	11.73	3.34	6.67	7.15	15.19	23.65	7.56	5.30	13.82
4	2014.00	4.82	11.93	2.98	5.79	8.77	13.77	23.42	6.67	6.93	14.91
5	2015.00	4.43	11.11	3.58	5.93	8.95	14.31	23.54	7.06	6.59	14.50
6	2016.00	7.70	13.60	3.63	7.25	8.01	15.86	20.09	5.89	7.40	10.57
7	2017.00	4.41	13.77	4.13	6.61	8.54	15.15	20.11	8.82	6.06	12.40

Table A10: Emotion Distribution (%) by Year – Media Devices & Camera Gear (Cluster 6)

Year-over-Year % Change — Cluster 6.0

	year	anger	anticipation	disgust	fear	joy	negative	positive	sadness	surprise	trust
0	2010	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
1	2011	−1.12	0.56	−0.14	−2.38	0.0	−1.4	1.96	−0.42	3.5	−0.56
2	2012	0.52	−0.64	−0.21	−0.14	1.6	2.67	−2.06	1.16	−3.5	0.62
3	2013	1.16	1.73	0.75	0.37	−2.85	−0.37	1.06	0.52	−1.0	−1.37
4	2014	−0.78	0.2	−0.36	−0.88	1.62	−1.42	−0.23	−0.89	1.63	1.09
5	2015	−0.39	−0.82	0.6	0.14	0.18	0.54	0.12	0.39	−0.34	−0.41
6	2016	3.27	2.49	0.05	1.32	−0.94	1.55	−3.45	−1.17	0.81	−3.93
7	2017	−3.29	0.17	0.5	−0.64	0.53	−0.71	0.02	2.93	−1.34	1.83

Table A11: Year-over-Year Change in Emotion Distribution (%) – Media Devices & Camera Gear (Cluster 6)

Emotion Distribution (%) — Cluster 9.0

	year	anger	anticipation	disgust	fear	joy	negative	positive	sadness	surprise	trust
0	2010.00	4.87	7.08	4.42	13.27	5.75	19.03	18.58	13.27	4.87	8.85
1	2011.00	17.28	4.94	0.62	7.41	4.32	25.31	19.14	8.02	6.79	6.17
2	2012.00	9.57	8.70	3.77	7.54	6.09	20.87	17.68	9.86	5.80	10.14
3	2013.00	9.17	10.80	3.17	5.83	6.86	17.65	22.88	7.11	4.71	11.83
4	2014.00	6.64	11.58	3.94	8.03	6.95	14.98	19.61	8.65	6.72	12.90
5	2015.00	6.43	9.80	4.82	8.33	6.29	18.71	19.30	9.06	6.87	10.38
6	2016.00	7.45	10.55	4.08	6.89	6.89	15.61	23.21	6.47	8.02	10.83
7	2017.00	9.11	12.50	3.21	5.36	9.64	15.54	22.86	5.71	5.54	10.54

Table A12: Emotion Distribution (%) by Year – Charging Cables & Accessories (Cluster 9)

Year-over-Year % Change — Cluster 9.0

	year	anger	anticipation	disgust	fear	joy	negative	positive	sadness	surprise	trust
0	2010	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
1	2011	12.41	−2.14	−3.8	−5.86	−1.43	6.28	0.56	−5.25	1.92	−2.68
2	2012	−7.71	3.76	3.15	0.13	1.77	−4.44	−1.46	1.84	−0.99	3.97
3	2013	−0.4	2.1	−0.6	−1.71	0.77	−3.22	5.2	−2.75	−1.09	1.69
4	2014	−2.53	0.78	0.77	2.2	0.09	−2.67	−3.27	1.54	2.01	1.07
5	2015	−0.21	−1.78	0.88	0.3	−0.66	3.73	−0.31	0.41	0.15	−2.52
6	2016	1.02	0.75	−0.74	−1.44	0.6	−3.1	3.91	−2.59	1.15	0.45
7	2017	1.66	1.95	−0.87	−1.53	2.75	−0.07	−0.35	−0.76	−2.48	−0.29

Table A13: Year-over-Year Change in Emotion Distribution (%) – Charging Cables & Accessories (Cluster 9)

Emotion Distribution (%) — Cluster 10.0

	year	anger	anticipation	disgust	fear	joy	negative	positive	sadness	surprise	trust
0	2010.00	4.86	9.73	2.70	5.41	9.19	16.22	25.41	7.57	4.86	14.05
1	2011.00	6.55	12.25	4.27	7.69	7.41	16.52	18.23	9.40	7.69	9.97
2	2012.00	5.29	11.06	1.92	6.73	9.13	13.94	24.04	7.69	7.21	12.98
3	2013.00	4.61	11.77	3.07	6.74	9.64	13.14	22.95	6.66	5.97	15.44
4	2014.00	7.43	11.32	3.35	6.70	9.60	13.86	22.37	6.79	6.25	12.32
5	2015.00	5.88	12.07	4.17	6.84	8.97	15.92	20.51	8.01	6.20	11.43
6	2016.00	5.13	11.09	3.49	6.98	8.42	14.78	23.00	10.06	4.72	12.32
7	2017.00	4.54	10.37	4.32	7.56	9.50	15.12	23.33	6.26	4.75	14.25

Table A14: Emotion Distribution (%) by Year – Remotes & Control Devices (Cluster 10)

Year–over–Year % Change — Cluster 10.0

	year	anger	anticipation	disgust	fear	joy	negative	positive	sadness	surprise	trust
0	2010	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
1	2011	1.69	2.52	1.57	2.28	−1.78	0.3	−7.18	1.83	2.83	−4.08
2	2012	−1.26	−1.19	−2.35	−0.96	1.72	−2.58	5.81	−1.71	−0.48	3.01
3	2013	−0.68	0.71	1.15	0.01	0.51	−0.8	−1.09	−1.03	−1.24	2.46
4	2014	2.82	−0.45	0.28	−0.04	−0.04	0.72	−0.58	0.13	0.28	−3.12
5	2015	−1.55	0.75	0.82	0.14	−0.63	2.06	−1.86	1.22	−0.05	−0.89
6	2016	−0.75	−0.98	−0.68	0.14	−0.55	−1.14	2.49	2.05	−1.48	0.89
7	2017	−0.59	−0.72	0.83	0.58	1.08	0.34	0.33	−3.8	0.03	1.93

Table A15: Year-over-Year Change in Emotion Distribution (%) – Remotes & Control Devices (Cluster 10)

Emotion Distribution (%) — Cluster 15.0

	year	anger	anticipation	disgust	fear	joy	negative	positive	sadness	surprise	trust
0	2010.00	7.14	6.35	5.56	10.32	5.56	23.02	17.46	11.11	5.56	7.94
1	2011.00	6.02	12.03	5.16	10.03	7.16	20.63	17.77	7.16	4.58	9.46
2	2012.00	10.45	9.55	2.99	9.25	7.46	16.42	17.31	8.96	5.97	11.64
3	2013.00	5.84	11.80	2.66	7.61	8.76	16.62	22.08	6.85	4.70	13.07
4	2014.00	7.19	11.22	3.15	8.27	7.09	16.93	19.29	8.66	6.50	11.71
5	2015.00	3.49	12.60	4.07	5.62	8.91	15.12	20.74	7.95	6.78	14.73
6	2016.00	2.01	14.43	2.01	5.03	11.07	11.41	25.50	6.38	7.72	14.43
7	2017.00	2.91	11.05	1.74	8.14	9.30	18.60	20.93	10.47	5.81	11.05

Table A16: Emotion Distribution (%) by Year – Budget Tech & Durability (Cluster 15)

Year-over-Year % Change – Cluster 15.0

	year	anger	anticipation	disgust	fear	joy	negative	positive	sadness	surprise	trust
0	2010	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
1	2011	-1.12	5.68	-0.4	-0.29	1.6	-2.39	0.31	-3.95	-0.98	1.52
2	2012	4.43	-2.48	-2.17	-0.78	0.3	-4.21	-0.46	1.8	1.39	2.18
3	2013	-4.61	2.25	-0.33	-1.64	1.3	0.2	4.77	-2.11	-1.27	1.43
4	2014	1.35	-0.58	0.49	0.66	-1.67	0.31	-2.79	1.81	1.8	-1.36
5	2015	-3.7	1.38	0.92	-2.65	1.82	-1.81	1.45	-0.71	0.28	3.02
6	2016	-1.48	1.83	-2.06	-0.59	2.16	-3.71	4.76	-1.57	0.94	-0.3
7	2017	0.9	-3.38	-0.27	3.11	-1.77	7.19	-4.57	4.09	-1.91	-3.38

Table A17: Year-over-Year Change in Emotion Distribution (%) – Budget Tech & Durability (Cluster 15)