Executive Summary

This project analyzed A total of 4,410 cleaned tweets were analyzed, covering 91 days for Lululemon and 7 days for Nike, to evaluate how users emotionally engage with and talk about Lululemon and Nike.

The results revealed two different brand images: Lululemon's dialogue was emotionally diverse and value-driven, with joy and optimism linked to lifestyle and wellness, and anger and sadness tied to service and ethics. Nike's conversation was more emotionally consistent and optimistic, reflecting a promotional, hype-focused tone centered on product drops and sneakers.

A hybrid sentiment model (VADER + RoBERTa) reclassified 1,600 mislabelled tweets, enabling more accurate sentiment-emotion insight. Topic modeling suggested that Lululemon's dialogue is driven by lifestyle, customer experience, brand advocacy, and wellness-related sustainability values, while Nike's is driven by sneaker culture, promotional hype, and product enthusiasm.User segmentation showed that Lululemon is supported by emotionally connected micro-influencers, who are integrated in conversational networks, whereas Nike's micro-influencers are mainly high-engagers, more attuned to trends.

Approach Breakdown

Data Cleaning & Preparation

As part of the preprocessing done to the dataset raw tweets were cleaned and standardized. Emojis were demojized using emoji.demojize() in order to preserve emotional cues in text format. Tweets were lowercased, and noise such as URLs, mentions, Hashtags and special characters were removed using regular expressions. A custom stopword list included the default NLTK English stopwords in addition to informal social media slang *(e.g., "lol", "amp")*. Language detection was utilized via "langid" library in order to retain only English tweets. Retweets were excluded based on text prefix filtering "RT". Noisy, spam promotional tweets were dropped using rule-based phrase detection *(e.g., "link in bio", "shop my closet")* and hashtag matching *(e.g., #poshmark, #shopmycloset)*. Additionally, Tweets from known promotional accounts, were also removed (e.g., @kinseyfit). Both copies of each tweet were retained in two duplicate formats: clean_text for sentiment and emotion modeling, and preprocessed_text for topic modeling, which was additionally lemmatized and tokenized.

Sentiment and Emotion Classification

The hybrid sentiment classification approach was used to address the limitations of pre-defined models. VADER tool was used for it's ability to analyze short social and informal text like Tweets (Hutto and Gilbert, 2014). This provided initial sentiment tags (positive, neutral, negative). While it worked well in identifying general tone, it did not perform well detecting complex expressions like sarcasm and passive aggression **(Figure 1)**.

To provide additional depth an emotional layer was added. RoBERTta (cardiffnlp/twitter-roberta-base-emotion model) was used to detect one out of four emotions: joy, optimism, sadness, or anger. This added some context, but introduced new conflicts—like misclassifying some tweets in cases where the sentiment was opposite *(e.g., "anger" = "positive")*. For further validation, a review of a stratified sample of tweets was conducted and missclassified tweets where labeled manually. Which revealed additional misclassification patterns and supported the hybrid correction process.

A custom hybrid approach adressed these errors using the following logic:
- Joy/optimism + positive sentiment = positive
- Anger/sadness + negative sentiment = negative
- Anger/sadness + positive sentiment = negative
- Conflicting or ambiguous cases defaulted to neutral

This reclassified 38.7% of Lululemon tweets and 23% Nike tweets, correcting sentiment skew due to sarcasm or emotional nuance. The method was selected to provide a more accurate and emotion-enhanced results.
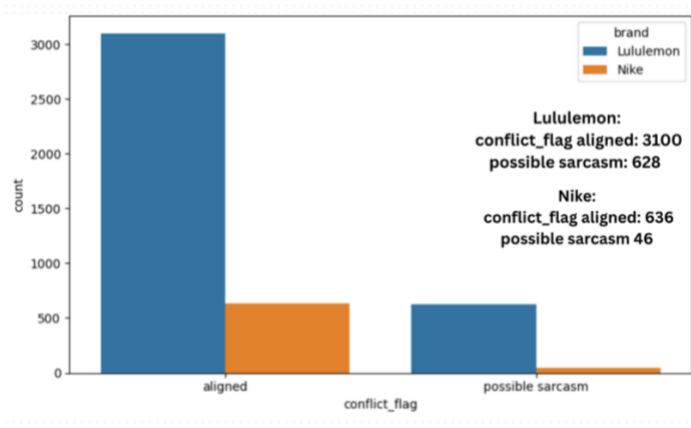

Figure 1 Sentiment-Emotion Conflict

Topic Modeling (LDA)

To determine the top topics for each brand Latent Dirichlet Allocation (LDA) was used and trained with default parameters to ensure consistent topic convergence and coherence across both brand datasets (Blei, Ng and Jordan, 2003). Initially the topics had some emoji-like text *(e.g., smilingfacewithhearteyes)* that got removed to reduce noise. Tweets were tokenized and lemmatization using spaCy and NLTK. Bigrams were formed using Gensim's Phraser() in order to capture key expressions (*e.g., customer_service, Nike_air) (Řehůřek and Sojka, 2020)*. Tweets containing less than three words were removed to ensure meaningful full-sentences. Rare tokens appearing in fewer than three tweets were filtered out, and a custom stopword list was used to remove vague and obvious terms like "many," "good", "nike" to improve interpretability. A Gensim dictionary and bag-of-words corpus were created from the cleaned tokens for model training.

In order to determine the number of topics, coherence score measurement was used **(figure 2)**. Supported by these results, four topics for both Lululemon (coherence ≈ 0.45) and Nike (coherence ≈ 0.58) was selected. The top keywords per topic were reviewed, and topic names were manually assigned through a combination of keyword inspection and tweet validation *(e.g., "sneaker, available, size" or "renewable_energy, coal_pollution, transition_company")*. Manual labeling of top tweets per topic was used to ensure consistency, sentiment-topic, and emotion-topic cross-tab analysis was applied to examine dominant polarity and emotional expressions within each cluster.
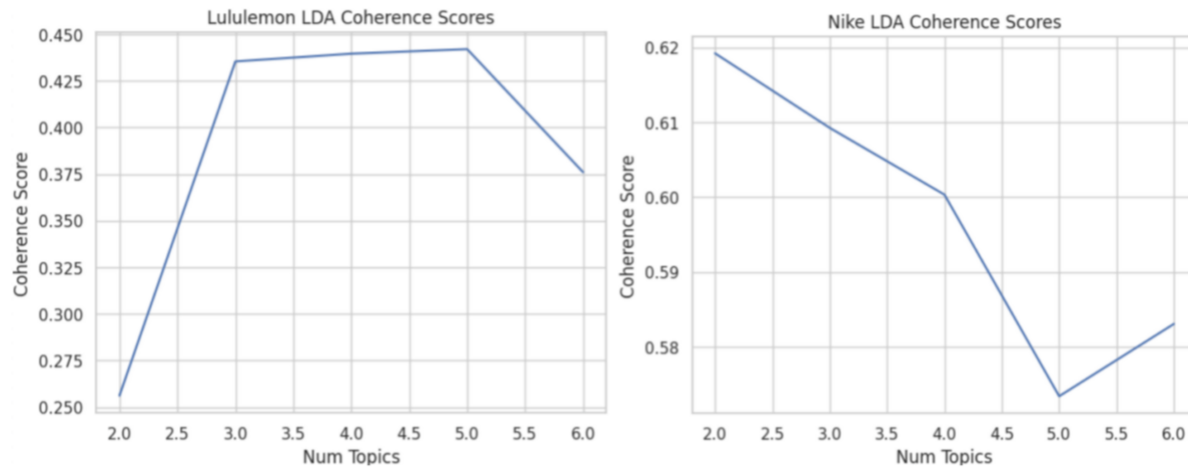
Figure 2 LDA Coherence Analysis

User Type Classification

In order to better understand users engaging with each brand, a rule-based classification system was used. Users were segmented into five groups based on followers, friend ratio, verification status and profile metadata: Public Figures/Brands, Micro-Influencers, Highly Social Users, General Users, and Others. Segmentation allowed the separation of high-profile influencers, and everyday consumers. These user profiles illuminated differences in brand community structure and were then used to filter micro-influencer candidates.

Micro-Influencer Detection

Micro-influencer candidates were identified using engagement metrics and profile characteristics. It included users having 1,000–50,000 followers, two or more tweets relevant to the topic, and total engagement (likes + retweets) ≥50. Engagement rate was normalized to follower count for fair comparison between varying sizes accounts. Secondary filters included follower-to-friend ratio ≥0.5 to make sure that audience quality is credible, and positive hybrid sentiment label throughout. Brand-associated accounts *(e.g., "ceo"),* suspected bots, numeric handles, and known other brand-associated accounts *(e.g., @calvinmcdonald)* were excluded. Finally, to ensure that each influencer-ID appears only once in the final shortlist a de-duplication step was taken. Nike's micro-influencer identification used the same criteria but with structural adjustments according to metadata differences *(e.g., author_id).* These steps ensured a shortlist of authentic, high-potential advocates with meaningful audience engagement, suitable for collaborations.

Network Analysis

Mention networks were constructed for both brands using directed graphs to understand user interaction behavior. @mentions were extracted, and each mention was modeled as a directed edge from the author (source) to the mentioned user (target). These edges were then used in brand-specific graphs using the NetworkX library (Hagberg, Swart and Chult, 2008). For each brand, degree and betweenness centrality were computed to evaluate user importance and position in the network. Additionally, to further understand communication patterns and important users, a subgraph of the top 50 highest-degree nodes was visualized using a spring layout. Network density and average clustering coefficient were also calculated to get structural insights. Interaction types (reply, mention, original) were classified separately to support comparison of users behavior across brands and investigate whether the conversations are two-way or broadcast-like.

Data Description

This comparison was drawn from two datasets obtained from Twitter, which picked up on public talk around topics like sport and lifestyle brands of Lululemon and Nike. For Lululemon, the data was a longer three-month period between October 1, 2021 and January 1, 2022, that originally contained 6,190 tweets, averaging nearly 41 tweets per day, narrowed down to 3,728 tweets from 2,863 unique users after pre-processing. For Nike, the data was scraped over a period of 7 days from February 23 to March 3, 2023, with 3,000 tweets, averaging nearly 97 tweets per day of which 682 tweets from 334 unique users remained. Nike's engagement rate was higher compared to lululemon (7 vs

3.55). Each tweet also retained related metadata including user ID, follower count, likes and retweets. Along with derived features like sentiment, emotion, topic label, engagement rate, and user type. Although geolocation data was unreliable due to high number of null values, available locations were kept where present to avoid losing valuable insights. Additionally, to enable cross-branding comparison, both data sets were formatted as normalized Pandas DataFrames. Despite temporal misalignment, both data sets are rich and insightful providing sufficient coverage for reliable snapshot analysis.

Brand Exploration

Sentiment, Emotion, & Engagement Analysis

As shown in **(Figure 3),** the hybrid sentiment analysis—built by combining VADER sentiment labels with RoBERTa emotion predictions—revealed substantial shifts in sentiment interpretation, particularly for Lululemon. A total of 1,441 tweets (38.7%) for Lululemon and 157 tweets (23%) for Nike were reclassified due to skewness in the original VADER analysis, where sarcasm, passive-aggressiveness, irony, and emotionally charged ambiguous content were consistently misclassified as positive or neutral. For example, tweets like *"@lululemon why do you make shorts without pockets"* were previously labeled as positive, despite clearly having a critical tone. These cases were better addressed by the tuned hybrid model, which resulted in a decrease of positive sentiment by 31.1% and an increase in negative sentiment by 64.1% for Lululemon. This shift revealed user dissatisfactions, typically related to delivery or ehtical issues (e.g., recycling). On the other hand, Nike's sentiment profile was more consistent, showing a 15.6% drop in positive sentiment and a small rise in tweets labeled as neutral or negative, which reflects Nike's promotion-oriented, hype-driven tweet culture that is less likely to include uncertainty compared to the community-driven tweets for Lululemon.
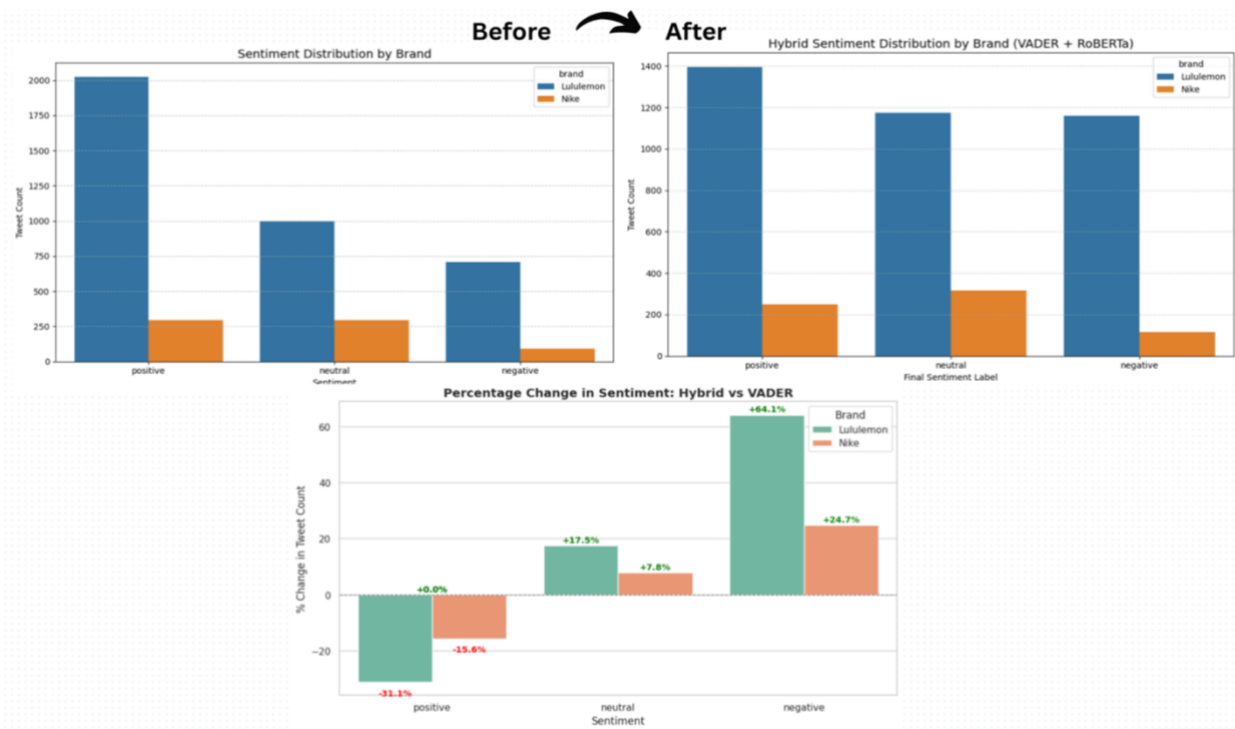
These corrections were crucial for accuracy, and understanding deeper emotional meaning behind tweets. For example a Nike tweet labeled as "sadness*"—"Day 23. When I started 'hoarding' shoes there were no rules, no logic, just vibes.*"—actually reflects excitement and joy in a sarcastic way. Yet, it was initially tagged as sadness due to its phrasing. This misalignment highlights how the emotion or sentiment classifier alone can lead to a distorted picture of public sentiment, making this approach better in avoiding miss-interpretation of public view.

Figure 3 Sentiment Shift after using Hybrid Model

As seen in (**Figure 4)**, engagement patterns (likes + retweets) showed that, for both brands, tweets with positive sentiment received the highest average interaction (4.26), followed by neutral (4.14), then negative tweets (3.50). Suggesting that content expressing emotion (particularly positive ones) attract engagement. Nevertheless, even negative tweets received substantial interaction, which highlights the importance of emotional diversity in stimulating conversations. Nike's, was mainly optimistic, with product-related tweets, though occasional emotional spikes linked to critique also drove some engagement.

Additionally, emotion-level breakdown revealed that Lululemon and Nike trigger different emotional responses. Lululemon tweets expressed a broad range of emotions—joy (1,081), optimism (1,487), sadness (778), and anger (382) showing emotional authenticity, reflecting its wellness and community-centric brand voice. Nike's emotional report was far more homogeneous: optimism (473 tweets), joy (93), sadness (83), and anger (33). Although optimism drove volume at Nike, peak average engagement actually came from its less frequent emotions: sadness (10.98) and anger (7.42).
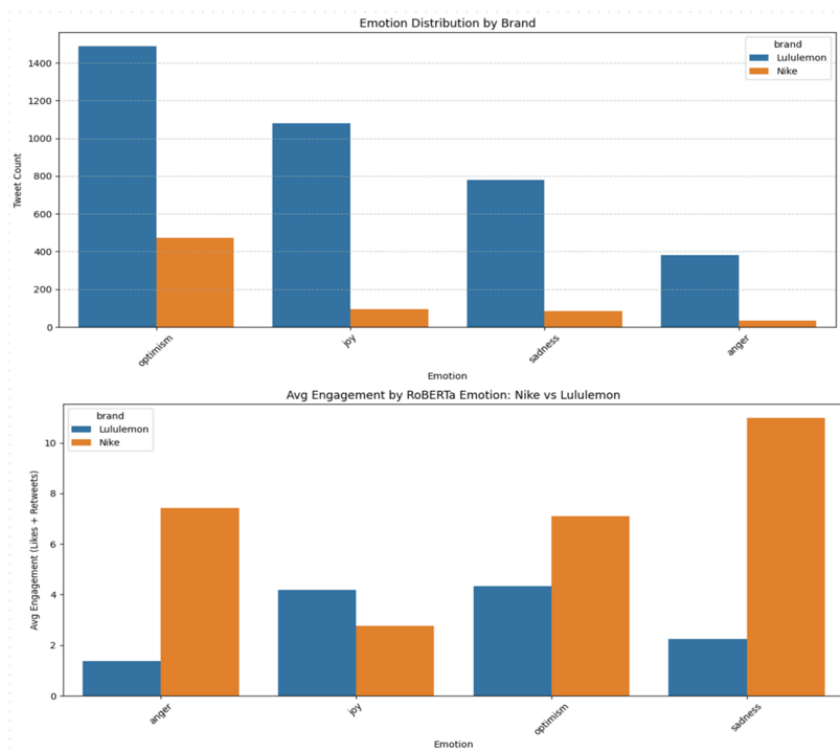

Figure 4 Emotion Distribution vs. Engagement

Finally, **(Figure 5)** in the sentiment-engagement scatterplot both brands display emotionally driven engagement profiles. This suggests that tweets expressing strong sentiment—whether positive or begative—drive higher interaction. Meaning that emotional diversity is important for user engagement and attention.
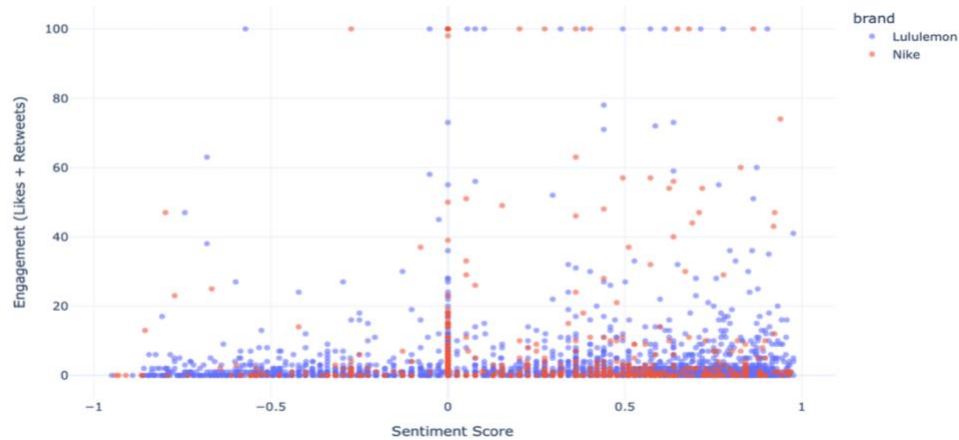
Figure 5 Sentiment vs Engagement scatterplot

Topic, Hashtag, and Thematic Analysis

Topic modeling of the LDA results revealed both brands' most common topics in user discussions. For Lululemon, four topics were identified: Product & Customer Experience (1,048 tweets), Sustainability and Ethical Topics (528), Advocacy, Access & Brand Loyalty (791), and Wellness & Product Fit (385). The top keywords for these topics included terms such as pant, legging, order, customer_service, ditch_coal, and renewable_energy, highlighting a mix of product use, service expectations, advocacy, and ethical discourse. These themes captured tweets related to product satisfaction, service interactions, moral alignment, and wellness-oriented brand perception.

For Nike, four topics were also identified: Sneaker & Brand Opinions (109 tweets), Dunk Low Style & Hype (97), Product Drops & Performance (123), and Sneaker Reviews & Promotions (120). The top keywords for these topics included dunk_low, retro, size, style, and training_jogger, highlighting a focus on product launches, limited-edition drops, athletic performance gear, and consumer style preferences. These themes captured tweets related to sneaker hype, cycles of trend-contents, performance wear, and product reviews **(Figure 6).**
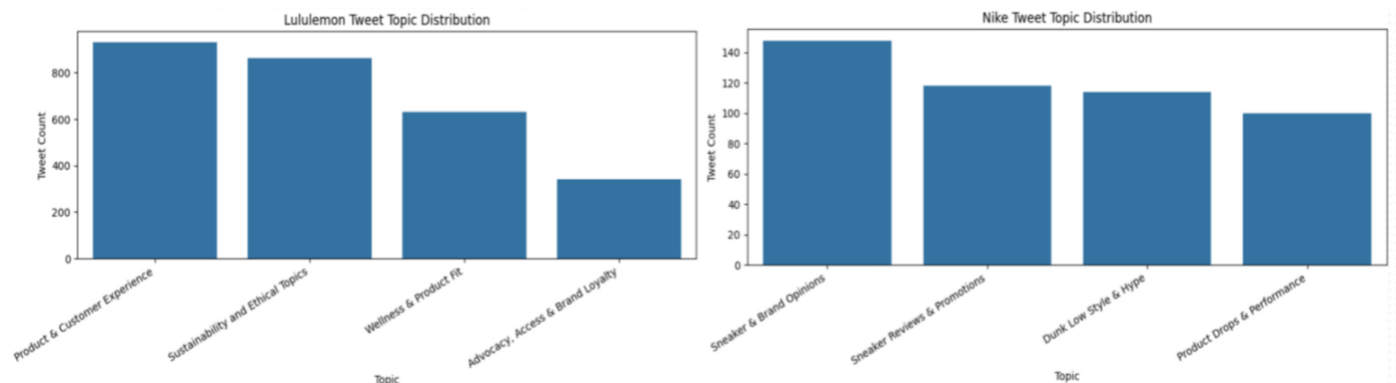

Figure 6 Topic Distribution

A cross-tab between topics and emotions **(Figure 7)** helped in further understanding how users feel and engage with each topic. For Lululemon, "Sustainability and Ethical Topics" had the highest rate of anger, showing frustration or skepticism toward ethical matters. In contrast, "Product & Customer Experience" and "Advocacy, Access & Brand Loyalty" showed more joy and optimism, reflecting the positive emotional alignment with the brand's lifestyle and values. "Wellness & Product Fit" showed a more neutral emotional profile, with a mix of frustration and product satisfaction.

For Nike, emotion toward topics was mostly optimistic, with less sadness or anger. This emotional consistency enhances engagement volume but also reflects a relationship with the brand, centered around product drops and excitement rather than value-based affiliation.
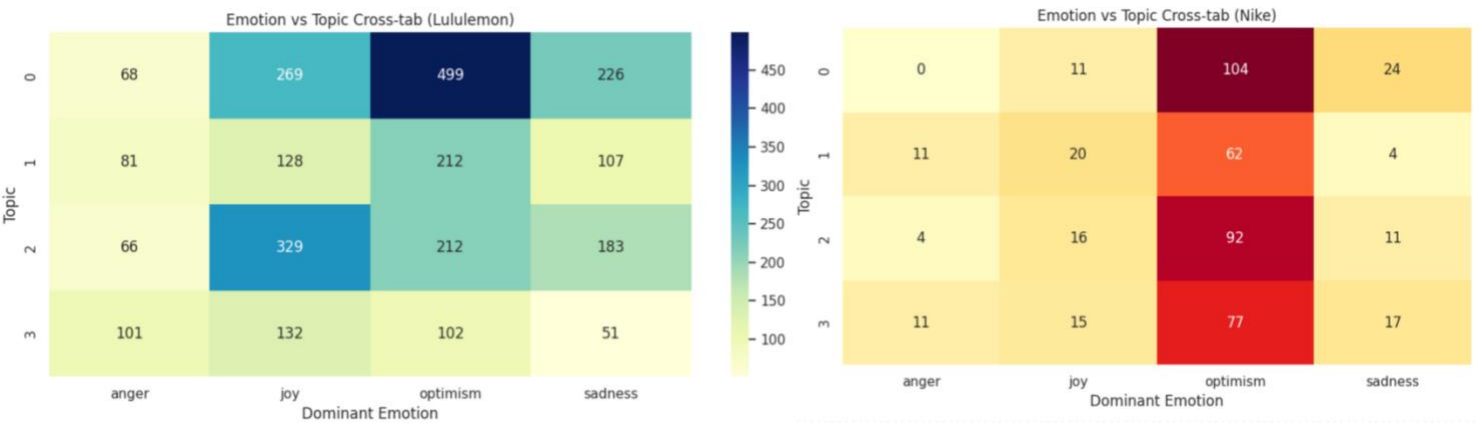

Figure 7 Emotion-Topic Heatmap

Additionally, topics and sentiment were also analyzed, which reinforced this pattern: Lululemon's "Sustainability and Ethical Topics" had the highest share of negative sentiment (39.5%), while Nike's topics in general maintained consistent neutral–positive sentiment, with up to 45% of tweets labeled positive. This suggests that Lululemon's audience expresses a wide set of emotions and engages in value-driven conversations that blend appreciation with scrutiny, whereas Nike's discourse remains more consistently optimistic, performance-oriented, and hype-driven.

Types of Users & Interaction Networks.

To understand who drives brand conversations on Twitter, users were segmented into five categories and classified based on criteria mentioned earlier (Section 2.4). The resulting typology revealed two very different communities. Lululemon's audience were more community-oriented, with 44.1% general users, 29.1% micro-influencers and 24.6% highly social users. Nike's audience was wider and more passive, comprised of 56.9% general users, 23.5% micro-influencers, and fewer Highly Social Users (14.5%) **(figure 9)**. This reflects each brand's voice, and platform use, where Lululemon is built on relationship, and community engagement, and Nike's tweets are for reach and broadcasting drops and trends.
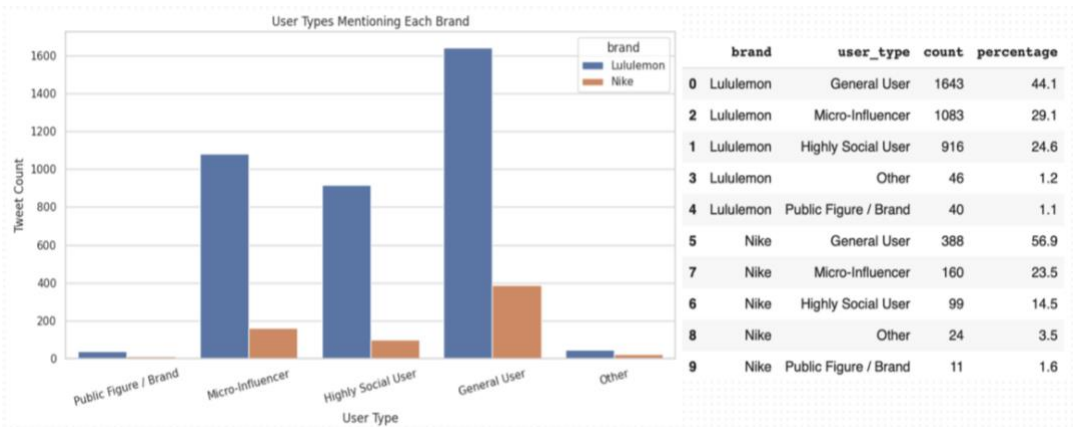

	brand	user_type	count	percentage
0	Lululemon	General User	1643	44.1
2	Lululemon	Micro-Influencer	1083	29.1
1	Lululemon	Highly Social User	916	24.6
3	Lululemon	Other	46	1.2
4	Lululemon	Public Figure / Brand	40	1.1
5	Nike	General User	388	56.9
7	Nike	Micro-Influencer	160	23.5
6	Nike	Highly Social User	99	14.5
8	Nike	Other	24	3.5
9	Nike	Public Figure / Brand	11	1.6

Figure 8 Summary of user types

While Public Figures had the highest average engagement for Lululemon (48.75), Nike's highest engagement group was Micro-Influencers (20.36). Across both brands, micro-influencers showed the strongest mix of interaction and

authenticity. Lululemon's micro-influencers averaged 5.09 engagements per tweet, and Nike's performed even better at 20.36 **(Figure 10)**. However, there was no significant correlation between follower count and engagement rate for either brand (Lululemon: r=0.558, p=0.62; Nike: r =–0.849, p= 0.35), suggesting that high visibility doesn't guarantee meaningful engagement. Interaction type breakdown reinforced these differences, where Lululemon had 63.4% replies and 36.3% mentions, showing a two-way communication dialogue. Nike's tweets were mostly direct tweets (75.5%) showing its promotional, product hype style. **(Figure 9).**

	brand	user_type	engagement
3	Lululemon	Other	53.76
4	Lululemon	Public Figure / Brand	48.75
2	Lululemon	Micro-Influencer	5.09
1	Lululemon	Highly Social User	1.78
0	Lululemon	General User	1.01
7	Nike	Micro-Influencer	20.36
9	Nike	Public Figure / Brand	6.91
6	Nike	Highly Social User	5.70
8	Nike	Other	2.62
5	Nike	General User	2.09

interaction_type	Lululemon	Nike
reply	63.4	5.4
mention	36.3	19.1
Tweet	0.2	75.5

Figure 9 Interaction type Summary

Figure 10 Engagement Per User Type

Network analysis further clarified how micro-influencers interact with their communities. For Lululemon, only one influencer *(@_dawnmontgomery)* received inbound mentions, showing active participation in the community's online conversations, suggesting that they're engaged in brand-related dialogue. On the other hand, none of Nike's micro-influencers were mentioned by others, aligned with their role as content broadcasters. Despite stronger engagement metrics, their influence is more isolated and campaign-oriented since they all had 0 betweeness and centrality.

Micro-Influencer Recommendation

To find credible micro-influencers, previously defined criteria (Section 2.5) was applied along-side sentiment, tone, engagement, profile credibility, and network centrality to identify reliable, authentic users for both brands and recommend one high potential micro-influencer for each brand. For Lululemon, *@_dawnmontgomery* shows best potential with 11.1K followers, two brand-relevant tweets, and a total engagement of 55 (engagement rate: 0.0025). Despite having a comparatively lower engagement rate, *@_dawnmontgomery* received four inbound mentions, showing engagement and embededdness within Lululemon's conversational network. The user's tweets are emotionally relatable and community-oriented, for example: *"I need a @lululemon gift card. $500 will do."* Although @2kaRask (highest engagement rate: 0.0138) and @ToriTidwell (positive customer service appreciation tweet) are strong alternatives, Dawn demonstrated social integration and authenticity, making them the best-fit for an ambassador-style partnership, focused on community loyalty and value alignment. For Nike, the strongest recommendation is user with ID *@1.45e+18*. Having 2.4K followers, three brand-related tweets, and a staggering total engagement of 778 (engagement rate: 0.1093), showing high resonance with Nike's trend-driven culture. Their posts reflect the sneaker hype aesthetic needed for reach, for example: *"I will do the same like the male fan, keeping the Jiyong signed shoes in a glass-box with a carpet grass⬚😂#NIKE ✔"*. Despite having no direct mentions, their high visibility, emotional tone, and community alignment makes them a strong candidate. Other users like *@1.2e+18* (0.0184 engagement) and *@108390895.0* (0.0087 engagement) also show potential but with comparatively less influence. Both suggestions align well with the respective communication strategy of each brand—Lululemon's being relational, reflective, and value-driven, while Nike is centered around visibility, hype, and cultural resonance.

Conclusion

This analysis focused on understanding how Lululemon and Nike are perceived and emotionally experienced on Twitter. Using sentiment and emotion classification, topic modeling, user segmentation, and network analysis, distinct brand identities and communities were identified. Lululemon's dialogue was emotionally diverse and value-based, with joy and optimism linked to wellness, lifestyle and products, sadness and anger linked to service and ethics. Which pointed to a relationship-based brand voice, supported by high reply rates and deep conversations. On the other hand, Nike's tone was more trend-based, showing optimism and hype. While this created high engagement spikes, emotional diversity and interactivity were low because of their promotional, shorter dataset. These distinctions were confirmed with topic modeling and micro-influencer analysis. Lululemon's topics focused on service, ethics, and lifestyle, and its micro-influencers were engaged in community dialogue. Nike, in contrast, focused on sneaker culture, virality, and style, supported by high-impact, loud micro-influencers who drove reach more than relational depth.

To extend this pilot study into a full analysis, it's recommend to extend Nike's dataset to match Lululemon's 90-day dataset for a more balanced temporal comparison. Collect useable geolocation data to get deeper contextual insights that would be useful for regional campaigns. Expand to other platforms like (Instagram, Reddit, or TikTok) for a fuller view of cross-channel brand sentiment. Finally, mapping sentiment shifts over time to provide insight into how user attitudes change during product cycles and campaigns—allowing timely, targeted interventions and better emotional forecasting.

References

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