Global Knowledge, Memory and Commun

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Journal:	*Global Knowledge, Memory and Communication*
Manuscript ID	GKMC-02-2025-0098.R1
Manuscript Type:	Article
Keywords:	Social media, Material vs. experiential brands, Sentiment analysis, Customers, Customer Service

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1. Introduction

When scrolling through X (formerly Twitter) and witnessing interactions between customers and brand support accounts, a thread catches your eye expressing frustration with a newly purchased electronic gadget, while another expresses dissatisfaction with a recent vacation experience. As you explore these conversations, you start to notice a pattern: the tone and sentiment of these interactions change differently depending on whether the brand is related to material goods or experiential offerings. This study seeks to uncover the underlying dynamics of such interactions, analyzing how customer sentiments shift from initial complaints to subsequent exchanges.

The growing popularity of social media has created several opportunities for businesses to communicate with their existing or potential customers (Adeola *et al.*, 2020). Taking the right actions on social media helps brands efficiently manage customer complaints, fostering brand loyalty (Chierici *et al.*, 2018), brand engagement (Dapko *et al.*, 2021), and customer satisfaction (Zhao *et al.*, 2020). However, measuring customer satisfaction for experiences, such as the atmosphere at a concert, remains challenging (Gilovich and Gallo, 2020). Therefore, recent studies have operationalized different methods, such as text-mining and sentiment analysis, to reveal customer sentiment toward products and services (e.g., Chang *et al.*, 2023; Trivedi and Singh, 2021). Still, comparative studies between experiential and material purchases on customer sentiment remain limited (Park *et al.*, 2023).

Existing research shows that consumer reviews and electronic word of mouth (e-WOM) vary depending on the purchase type (Bastos and Moore, 2021; Al-Natour and Turetken, 2020; Bae and

Lee, 2011; Weathers *et al.*, 2015). In this context, Basu (2018) emphasizes the need in the customer satisfaction literature to investigate experiential and material products. Yet, little is known about how consumer sentiments evolve in social media conversations with support accounts, particularly when distinguishing between material and experiential purchases. As consumers increasingly complain on social media, brands must effectively de-escalate negative arousal in text-based interactions to ensure successful service recoveries (Herhausen *et al.*, 2023). Timely responses and appropriate messaging can transform negative sentiments into positive ones, ultimately enhancing customer satisfaction (Sashi *et al.*, 2019).

In this study, we argue that consumers' sentiments differ by brand type (material vs. experiential), requiring differentiated strategies to handle consumers' complaints on social media. We aim to uncover the underlying dynamics of customer interactions on brands' social media accounts, analyzing how customer sentiments shift from their initial complaints to subsequent exchanges using real-life online data of customer support requests in the form of support account tweets. This study also explores the factors to consider in predicting consumers' sentiments from their shared messages posted on brands' social media support accounts.

Specifically, we investigate the tweet sentiment evolution of customer complaints on X in experiential versus material brands, as well as the trends of the conversations, and the effects of conversation length, tweet character length, calendar effect, tweet content (i.e., links, pictures, videos, emojis), and engagement metrics (i.e., retweets, favourites, replies). This study aims to provide insights and propositions to brands on how to handle customer complaints posted on social media.

2. Literature Review

2.1. Customer Satisfaction and Sentiment

Customer satisfaction refers to the individual's subjective positive assessment of the outcomes and experiences linked with product consumption (Calvo-Porral and Otero-Prada, 2021; Oliver, 1977). Understanding customers' emotions is crucial for evaluating their satisfaction or dissatisfaction with their consumption experiences. Hitl *et al.* (2024) emphasize that positive sentiments of customers expressed through social media posts can be a marker of their satisfaction. Nowadays, customers often share their opinions and emotions through brand accounts, offering brands the opportunity to analyze customer sentiment and gain insights into satisfaction dynamics during brand support interactions. In this context, after-sales support services play a critical role in enhancing customer satisfaction and loyalty (Ashfaq, 2019). After-sales service quality leads to increased satisfaction, which in turn drives repurchase intention, positive WOM, and favorable behavior (e.g., De Matos and Rossi, 2008; Fazlzadeh *et al.*, 2011).

Previous research on measuring consumer satisfaction relied on generalized satisfaction data, financial data, or loyalty indicators, often measured through surveys like the American Customer Satisfaction Index (ACSI, 2024). However, technological advances brought a shift from customer relationship metrics to customer engagement metrics (Ma *et al.*, 2022; Ibrahim *et al.*, 2017). De Haan (2020) highlights the shift in measuring customer satisfaction from survey data to e-WOM and sentiment data, such as likes on Facebook or qualitative content analysis on social media. Consequently, online reviews became valuable sources for brands and researchers as indicators of customer satisfaction (Hitl *et al.*, 2024; Nilashi *et al.*, 2023; Zhao *et al.*, 2020). However, the full potential of social media data remains underexplored. For instance, Ren *et al.* (2018) demonstrate that negative reviews may not always correlate with reduced sales; in some cases, they can even boost sales. This highlights the opportunity to analyze how sentiment evolves during customer interactions, enabling businesses to develop strategies that transform negative sentiment into positive outcomes.

Customer emotions are not fixed outcomes but fluctuate throughout support exchanges, reflecting how emotions unfold dynamically across the course of the interaction (Verhulst *et al.*, 2020). Therefore, examining sentiment as it evolves within entire interactions can reveal patterns that single-point measures overlook. Research also shows that sentiment expression can vary across cultural and linguistic contexts (e.g., Dong, 2025), which may affect cross-market interpretations. Tracking the trajectory of sentiment, whether it improves or deteriorates, can provide valuable insights for successful service recovery.

2.2. Consumer Complaints

The literature on customer complaints increasingly emphasizes digital interactions between companies and customers, aligning with advancements in theorizing and measuring customer satisfaction (Zhang *et al.*, 2022; Stauss and Seidel, 2019; Einwiller and Steilen, 2015). This trend is driven by factors such as the impact of negative word-of-mouth (nWOM) and the rising tendency of customers to voice complaints online (Azemi *et al.*, 2020).

Companies follow various complaint-handling strategies, such as the 3T framework of timeliness, transparency, and trust (Stevens *et al.*, 2018). Davidow (2003) proposed six dimensions in strategic organizational responding, namely timely response, customer compensation, apology, explanation, attentiveness, and complainant support policies. However, large companies that handle complaints still do not seem to fully embrace social media opportunities. For instance, Einwiller and Steilen (2015) analyzed customer complaints and responses on the Facebook and X pages of large U.S. companies, finding moderate organizational responsiveness, with efforts often focused on redirecting complainants.

Hwang and Mattila (2020) investigated the impact of compassion on face-to-face complaints and online review posting behaviors following a service failure and showed that while prosocial emotions (e.g., compassion) influence face-to-face complaints, they have little impact on online review posting. Similarly, Blöndal (2017) investigated the consumer-generated content on Facebook and Twitter (now X) brand pages and demonstrates that consumers use Facebook brand pages to complain or ask questions, whereas X serves as a platform for not only complaining but also praising the brand.

2.3. Experiential versus Material Purchases

VanBoven and Gilovich (2003) identify experiential purchases as those primarily focused on acquiring life experiences, while material purchases are aimed at acquiring tangible goods or physical possessions. According to the experiential recommendation literature, there are various post-purchase advantages of experiential purchases compared to material ones, which would likely impact post-purchase support and online conversations. Experiential purchases seem to provide more happiness and satisfaction than material ones (Howell and Hill, 2009). Consumers of experiential products recall fewer negative experiences than material ones. For instance, regret from buying experiences is lower than regret from material purchases (Carter and Gilovich, 2010). Analyzing the differential regrets for material versus experiential purchases, Rosenzweig and Gilovich (2012) conclude that material purchase decisions lead to buyer's remorse (regrets of buying), while experiential post-shopping thinking involves missed opportunities (regrets of not buying). By examining the type of purchase (experiential vs. material) and consumers' feelings of envy, Park *et al.* (2023) demonstrate that when people compare well-being levels with others, experiential purchases elicit greater envy than material purchases.

Overall, consumers tend to rate experiential purchases higher than material purchases in terms of happiness, pleasure, and gratitude, considering them better financial investments (Pchelin and Howell, 2014; Thomas and Millar, 2013; Nicolao *et al.*, 2009). Building on previous research that operationalizes such favorable outcomes as a positive sentiment rather than a static state of well-being, our study attempts to fill gaps in marketing and consumer research concerning the sentiments of consumer complaints posted on brands' social media considering the distinction between material and experiential brands.

3. Hypotheses Development

The existing literature consistently demonstrates that experiential purchases provide more positive feelings in the aftermath than material ones. Individuals prefer experiential purchases as compensation for their previous bad experiences, such as work-family conflict (Ma *et al.* 2021). Experiential purchases also offer a more pleasant conversational value than material purchases (Kumar and Gilovich, 2015; Van Boven *et al.*, 2010), largely because participants make up stories and narrate them. Due to the story and narration value of experiences over materials, they tend to be shared more (Bastos and Brucks, 2017, Caprariello and Reis, 2013). As the experiential recommendation literature predicts happier customers over time of experiential (vs. material) consumption, we expect conversations with the support accounts of experiential (vs. material) brands to have more positive sentiment overall. Therefore, we form our hypothesis as follows:

H1. Customers of experiential brands express significantly more positive sentiment in their tweets to support accounts compared to customers of material brands.

Furthermore, we expect differences in the ongoing conversation between customers conversing with material versus experiential brands' support accounts. Bastos and Moore (2021) demonstrate that WOM regarding experiential (vs. material) products elicits more desired consumer reactions, such as purchase intentions, due to finding the content more substantive. Experiences are associated with short utility durations, whereas, in contrast, material products are related to long utility durations (Weidman and Dunn, 2016). Drawing from the impatience asymmetry theory (Goodman *et al.*, 2019), since experiential brand customers would be more impatient when seeking support, we expect that their follow-up tweets to be more negative (compared to material brand customers). Therefore, for both material and experiential brands, we first examine how consumers' sentiments shift from their first to their second interaction with support accounts, which gives insight into how initial frustrations or issues are immediately alleviated (or not). Second, we investigate how their sentiment evolves from their first to their last interaction, which reveals if consumers' initial negative or positive sentiments are sustained, become more positive, or more negative following their interaction with brands' support accounts. Therefore, we form the following hypotheses:

H2. Experiential brand customers show a more negative change in sentiment from the first to the second tweet in their conversations with support accounts compared to material brand customers.

H3. Experiential brand customers show a more negative change in sentiment from the first to the last tweet in their conversations with support accounts compared to material brand customers.

This study is structured to first verify the hypotheses related to sentiment trends in consumer conversations with brand support accounts, distinguishing between material and experiential brands. Then, it examines the effects of tweet-related characteristics such as the tweet length in characters, the content embedded (emojis, links, GIFs, and videos), and the calendar effects on predicting the sentiments of the customers' complaints. Finally, this study explores how customers' sentiment level differ between material and experiential brands based on engagement metrics (i.e., retweets, favourites, replies), thread length, hours of positng, days of posting, number of characters in tweets, and tweet content, considered independently.

4. Method

Previous research used qualitative text mining (Lee and Hu, 2005), text analysis (Hu *et al.*, 2019), and narrative content analysis (Sparks and Browning, 2010) to analyze customers' online complaints and reviews. Einwiller and Steilen (2015) examined complaint posts and tweets posted by individual users on social networking sites, looking at patterns in threads starting with a complaint, responses, follow-up posts by complainants, and two posts by other users. Blöndal (2017) collected comments on brand pages on both Twitter (now X) and Facebook and categorized comments into six groups: complaints, issues, jokes, praises, questions, and suggestions. The author suggests that Facebook is used more for seeking advice and recommendations while X is more of a platform for consumers to vent their anger.

In this study, we employ sentiment analysis to automatically analyze the customer's emotional tendency by addressing the customer's post on social media (Yang *et al.*, 2020). X is a micro-blogging platform enabling real-time conversations and opinion-sharing via quick and short messages. X has unique characteristics, such as being public and customer service-oriented, making it ideal for investigating consumer engagement with brands (Gulati, 2021; Read *et al.*, 2019). Tweets reflecting opinions and sentiments toward brands can directly affect existing and potential customers' attitudes (Ibrahim *et al.*, 2017). Strategically, companies have the opportunity to analyze the consumer-generated content (CGC) available on social media (i.e., tweets and posts) to gauge customer feelings about products and services (Dhaoui *et al.*, 2017). Sentiment analysis helps identify and analyze the emotions expressed by customers on social media (Yang *et al.*, 2020), classify customer sentiment, and measure customer satisfaction (Khattak *et al.*, 2020), and thus gain a competitive advantage (Trivedi and Singh, 2021).

Using sentiment analysis and various statistical comparisons, we investigate the differences between material and experiential brands based on the sentimental changes in support account–customer tweet conversations. To this end, we first select brands to represent the two categories.

4.1. Research Design

To distinguish between experiential and material brands, we conducted two pilot studies where consumers rated brands as experiential or material. We followed a pre-test procedure (Aydin and Selcuk, 2019) where brands are selected from globally recognized practitioner reports (e.g., Forbes, Lovemarks) and academic literature (Gilovich and Gallo, 2020) listing top six experiential vs. material brandsThe experiential brands listed were The Walt Disney Company, KFC, McDonald's, Netflix, Starbucks, and Subway, while the material brands included Apple, Microsoft, IBM, The Home Depot, Louis Vuitton, and Nike. From this a priori pool, we retained brands that (i) operated a dedicated, publicly accessible, global (non-country) support handle active during the sampling window; (ii) had sufficient activity/visibility (minimum order-of-magnitude threshold for followers and historical tweets; ~100k as a guideline); and (iii) exhibited unambiguous category classification in our pilots. Brands failing these criteria were replaced by nearest category substitutes that met them. The first pre-test was administered to 56 business faculty students (Mage: 34.34, 35 females) at a European university for initially testing a total of

15 brands. After defining material and experiential products, participants rated each brand on a 7-point bipolar scale (1: material to 7: experiential). Please refer to Supplementary Table S1 for the results of this pre-test.

We conducted a second pilot test using a sample of 98 (mean age: 22.18, 63 females) among business faculty students at a European university. We were also cautious about having an equal number of material vs. experiential brands in the main study. Please refer to Supplementary Table S2 for the results of the second pre-test. Finally, in line with two pilot tests and purification according to the criteria, we decided to retrieve. The final set comprised three experiential (Netflix, Uber, Airbnb) and three material (Apple, Samsung, OnePlus) brands. Table 1 shows X account details of the selected brands, the total number of tweets posted, and the number of followers as of November 2020.

Insert Table 1 here

Insert Figure 1 here

The research design (Figure 1) illustrates the comparative analysis of customer sentiment using data from social media support accounts of experiential brands (@AirbnbHelp, @Netflixhelps, @Uber_Support) and material brands (@AppleSupport, @SamsungSupport, @OnePlus_Support). The study employs sentiment analysis and regression analysis to identify trends, factors influencing sentiment, and patterns of sentiment change in the two brand categories. Key metrics include engagement (retweets, favorites, replies), tweet characteristics (length, embedded content), calendar effect (posting day and hour), and thread length, providing a comprehensive approach to understanding customer sentiment dynamics.

4.2. Main Study

The first step of data collection is extracting selected brands' tweets and replies from X using customized Python software, combining web crawling and X API (Application Programming Interface). To collect the tweets, we used @username "mention" option with custom search parameters, ensuring only tweets mentioning the selected brands in our research sample. For example, we used @AirbnbHelp search query to gather tweets that only mention Airbnb, posted by the brand itself or by customers.

The next step is data cleaning which involves removing duplicate entries, irrelevant content, and excessive punctuation. Then, we conduct sentiment analysis on the retrieved X data to identify the emotional tone within the tweets, classifying them as positive, negative, or neutral. Following Al-Natour and Turetken (2020), we use Google Cloud Natural Language API for its reliability and consistency compared to other SA tools. The emotional intensity of the tweet contents was determined through the API provided using Google's Natural Language Processing library. We model sentiment scores as a continuous variable, which offer more analytical flexibility than binary or categorical classifications. Continuous scores allow us to perform different computations and analyze variance, enabling comparisons even within the same sentiment category (Al-Natour and Turetken, 2020; Kirilenko et al., 2018).

We analyzed each tweet individually and obtained the tweets' sentiment scores and magnitudes. The API service provides a "score" (emotional tone), "magnitude" (emotional intensity), and "language" (text language) for each tweet. The sentiment score of a tweet reflects the overall emotion, ranging from -1.0 (negative) to +1.0 (positive), and varies for each tweet. The magnitude indicates how much emotional content is present within the tweet, ranging from 0 to infinity. The text becomes negative as the sentiment value decreases, while the text becomes positive as the value increases. Google interprets scores between -1.0 and -0.25 as negative, 0.25

to 1.0 as positive, and -0.25 to 0.25 as neutral (Google Cloud, 2024). A sub-sample 5% of the dataset, was randomly selected for human validation (Lappeman *et al.*, 2020) to assess the tone of the sentiment as negative, positive, or neutral, ensuring the accuracy of the sentiment measurement. Percent agreement between human labels and Google's Natural Language Processing outputs exceeded 80%, indicating a high degree of alignment and reliability (Hutto and Gilbert, 2014).

4.2.1. Descriptives of the Dataset

We examine tweets posted by X accounts to the official support account of the six selected brands. To ensure consistency, we collected 10000 tweets from each accounts, resulting in a final sample of 60000 tweets (31843 customer tweets, 28157 corporate response tweets). The dataset size is consistent with prior research in sentiment analysis of X data (Ruz *et al.*, 2020). Table 2 revealss the metrics related to the number, length, frequency, time, content, and sentiment of the 10000 tweets retrieved from each of the selected brands' customer and support accounts. The average sentiment of customer accounts varies from -0.25 to -0.1, indicating that customers' sentiment is more negative than the sentiment of the support accounts. The average sentiment of the brand support accounts is neutral, except for Samsung, with positive sentiment of 0.27.

Insert Table 2 here

The length of the text is a critical factor, yet largely ignored in the sentiment analysis methodology (Al-Natour and Turetken, 2020). Tweets in our dataset average 461 characters in length. The longest customer tweet (671 characters) and the longest support account tweet (488 characters) both belong to Samsung. The shortest tweets belong to customers (4 characters), suggesting that the support accounts reply to customers' complaints with longer tweets.

Wednesday is the most frequently tweeted day for most (four out of six) brands in our dataset, and the most frequently tweeted hour is between 11.00 and 11.59 (EST).

Regarding content, support accounts share more links than customers, averaging 1829 total links compared to only 238. This is expected since links can provide solutions to customers' complaints or are part of automatic corporate replies. In contrast, customers share more embedded media than support accounts, including pictures (an average of 493 vs. 4), videos (an average of 37 vs. 7), and GIFs (an average of 48 vs. 10), which can be explained by customers' need to demonstrate the problems experienced with products.

5. Findings

In this section, we first test our hypotheses regarding the differences between experiential and material brands' customer tweets to support accounts. Then, we investigate the trend in the incremental sentiment change within tweet threads. Additionally, we explore the sentiment of customer tweets to material vs. experiential brands support accounts based on contextual factors of hours and days of tweets, conversation length, tweet length (characters), tweet content (emojis, videos, pictures, GIFs, links), and engagement metrics (retweets, favourites, replies).

5.1. Calculating the Change in Sentiment

The variable we built our hypotheses upon is the sentiment and change in sentiment regarding customers' tweets to support accounts. To prepare the data for testing, we first group tweets by threads, then isolate customer tweets and link each to the root tweet (tweet number 1). Google Cloud Natural Language API provides a score representing the sentiment for each tweet. We then compute the change in sentiment and order threads by their length, For each tweet thread, we provide the sentiment score for every tweet, the number of tweets in the thread, the highest sentiment score among the tweets in the thread, the lowest sentiment score, and the average sentiment per thread by dividing the total sentiment of the thread tweets by the number of tweets.

Then, we compute the sentiment change rate from the first to the second tweets, then from the second to the third tweets, and continue accordingly. Finally, we calculate the conversation sentiment change rate between the first and the last tweets, which gives us an insight into how the customer's sentiment has evolved throughout the conversation.

5.2. Hypothesis Testing

To test our hypotheses on sentiment differences between experiential and material brand customers' tweets, we analyze (1) the average sentiment of customer tweets, (2) the sentiment change between the first and last tweets, and (3) the sentiment change between the first and second tweets. We use t-tests to compare the two groups, specifically applying Welch's t-test due to unequal sample sizes. Our first hypothesis predicts that experiential brand customers' tweets to support accounts would have a more positive average sentiment than material brand customers. The analysis confirms the expectation, showing a significant difference in sentiment ($t(25207) = 6.887$, $p = .00$, $d = 0.09$) with a mean average sentiment difference of 0.307. Material brands' customers demonstrate more negative sentiments ($M_{mat} = -.209$, $SD_{mat} = .386$) compared to experiential brand customers ($M_{exp} = -.178$, $SD_{exp} = .326$).

Our second hypothesis proposes that experiential brand customers' tweets to support accounts would turn more negative in sentiment from the first to the second tweet compared to material brand customers. The results reveal a significant difference between the material and experiential brands ($t\ (4344) = -1.932$, $p = .05$, $d = -0.06$). The change in sentiment from the first to the second tweets is greater for material brands ($M_{mat} = .29$, $SD_{mat} = 1.97$) than experiential brands

(M_{exp} = .18, SD_{exp} = 1.71), indicating material brand customers' sentiment shifted more positively from the first to the second tweet.

Our third hypothesis predicts that experiential brand customers' tweets to support accounts would turn more negative in sentiment from the first to the last tweet compared to material brand customers. However, the results show no significant difference in sentiment change between material and experiential brands (M_{mat} = .29, SD_{mat} = 2.03; M_{exp} = .198, SD_{exp} = 1.74, t (4325) = -1.616, p = .11, d=-0.05). Table 3 summarizes Welch's t-test results.

Insert Table 3 here

In summary, hypotheses H1 and H2 were confirmed. Regarding the difference between the sentiment change from the first tweet to the last tweet of customers towards the support accounts of material vs. experiential brands, the results remain at the margins of significance (t (4325) = -1.616, p = .11), leading to the rejection of H3.

5.3. Additional Analyses on Material vs. Experiential Brands

To deepen insights, we analysed whether customer sentiment towards material and experiential brands varies with thread length, hour and day of posting, tweet length and content, and engagement metrics. Figure 2 shows the average sentiment by thread length for material and experiential brands.

Insert Figure 2 here

For experiential brands, longer threads exhibit a higher mean sentiment than shorter ones, whereas sentiment in material brand conversations fluctuates. A fitted trendline indicates a decline in sentiment for material brands as the number of tweets increases, supporting these differences in sentiment direction between experiential and material brand support account interactions.

Next, we calculated the average sentiment by posting hour sepeately for material vs. experiential brands. Even though the sentiment remains below zero (as expected in conversations with a support account), the sentiment level of customers of material brands is more negative than experiential brands, with two exceptions; from 5:00 to 6:00 AM and from 7:00 to 8:00 PM (EST) (see Figure 3). Overall, the sentiment level of material brands' consumers fluctuates more sharply with time compared to experiential brands that exhibit some stability in sentiment variation.

Insert Figure 3 here

Similarly, regarding the days of the week (see Figure 4), we find that customers of material brands demonstrate more negative sentiment than experiential brands, with the exception of Saturday, where both groups show equal sentiment scores (-0.19). Customers of material brands express significantly more negative sentiments on Thursdays (-0.30) and Fridays (-0.27).

Insert Figure 4 here

Figure 5 displays our analysis of the sentiment level by tweet length for material and experiential brands. We grouped tweets into five categories based on the number of characters they contain (0 to 50, 51 to 100, 101 to 150, 151 to 200, 201 to 280). Sentiment is more negative in longer tweets, suggesting that customers write longer tweets when they are experiencing strong negative feelings (e.g., anger). Customer tweets of material brands express the most negative sentiment (-0,25) when they write tweets that contain more than 101 characters, and the sentiment becomes more negative as the tweets become longer (-0.29 for tweets longer than 201 characters). In contrast, for customers of experiential brands, tweets convey a negative sentiment when they exceed 201 characters (-0.25). Overall, customers of material brands express more negative sentiments than those of experiential brands.

Insert Figure 5 here

Embedded content such as emojis, videos, pictures, GIFs, and links have various purposes and may represent different emotions depending on the product type. Our analysis regarding tweets containing GIFS, links, and videos in conversations to material vs. experiential brands support, experience category demonstrated an overall more positive sentiment compared to material brands (see Figure 6). In contrast, customers of material brands tweet with a more positive sentiment than experiential brands if the tweets include emojis or pictures (GIFs).

Insert Figure 6 here

We also examine whether customer sentiment differs between material and experiential brands based on engagement metrics, including favorites, retweets, and replies. Table 4 presents the engagement metrics for each brand.

Insert Table 4 here

Our analysis shows that customer sentiment differs between material and experiential brands based on engagement metrics—favorites, retweets, and replies. Material brand customers exhibit lower sentiment levels than experiential brand customers (see Figure 7). Overall, the sentiment is more negative in retweets than in favorites, and even lower in replies than in retweets. Replied tweets for material brands have a particularly negative sentiment (-0.25), indicating that tweets expressing negative sentiment are more likely to receive replies, whether from support accounts or other customers.

Insert Figure 7 here

5.4. Predicting Customer Sentiment

We considered several factors that may contribute to predicting customer sentiment, including embedded content (links, emojis, GIFs, videos, and pictures), tweet length, and posting time, estimating regressions separately for material and experiential brands.

The preliminary regression analysis results suggest that it would be possible to predict the sentiment of experiential products' customers based on the type of embedded content, tweet length, and days. For material brands, tweet length is the main predictor, and emojis are the only significant embedded-content type, with Tuesday, Wednesday, and Friday significant among days, while posting hour is not.

Given weak hour effects, we collapsed time into three categories: Early_Morning (00.00 - 05.59), Working_Hours (06.00 - 17.59), and Evening (18.00 - 23.59). We use "early morning" as a benchmark, in addition to Monday for Days and [0-50] for the Tweet Length. The final regression model is given in Equation (1).

$$Sentiment = \beta_0 + \sum_{k=1}^{5} \beta_{ec,k}\, Embedded\ Content_k + \sum_{m=1}^{4} \beta_{cl,m}\, Character\ Length_m + \sum_{l=1}^{2} \beta_{tp,l}\, Time\ of\ Posting_l + \sum_{i=1}^{6} \beta_{d,i}\, Days_i + \varepsilon \qquad (1)$$

Similar to the preliminary regression analysis, we reconduct the regression analysis for the experiential and material brands separately. The regression model yielded an adjusted R^2 of 0.091 for experiential brands and 0.080 for material brands. In the complex domain of consumer sentiment on Twitter, various factors influence sentiment changes (e.g., external events, user context). Low R^2 values, even below 0.1, are acceptable in social science research, so long as explanatory variables are statistically significant (e.g., Hassan *et al.*, 2020). The highly significant coefficients in our model (e.g., β for Emoji is 0.117 for experiential brands) demonstrate valuable insights into the effects of the parameters. Table 5 reports the coefficients of the final regression model.

Insert Table 5 about here

Results confirm all embedded content types are significant for experiential brands, but only emojis for material brands. Embedded content raises sentiment, while tweet length negatively predicts sentiment for both brands. While posting time is not significant, all days except Sunday are significant for experiential brands, whereas Tuesday, Wednesday, and Friday are significant for material brands.

6. General Discussion

In this study, we documented higher sentiment with experiential brands' support-related X posts. Sentiment declines with tweet length for both experiential and material brands. Longer threads lead to more negative sentiments for material brand customers, while they improve sentiments for experiential brand customers.

6.1. Theoretical Implications

This study shows that support-channel sentiment varies systematically by product category and that message/temporal features (embedded content, tweet length, day) provide useful insights for predicting sentiment. Findings align with prior studies demonstrating that experiential purchases provide a more pleasant conversational value than material purchases (Kumar and Gilovich, 2015; Van Boven *et al.*, 2010), and that consumers rely on online reviews for experiential purchases than for material purchases (Dai *et al.*, 2020), except when critique comes from close ties (Gilovich and Gallo, 2020). Accordingly, negative support sentiment may be less consequential for prospective experiential buyers due to weaker review influence.

The text length, a critical but underexplored factor in sentiment analysis literature (Al-Natour and Turetken, 2020), is highlighted as a key factor in predicting sentiment in customer support contexts. Beyond prior work on emojis (Boia *et al.*, 2013; Kralj Novak *et al.*, 2015), we show that all embedded content predicts customers' sentiment for experiential brands, whereas only emojis matter for material brands.

6.2. Managerial Implications

Our results suggest that material and experiential brands should adopt different online support strategies contingent on the demonstrated differences in customer sentiment. Based on a positive sentiment advantage, marketing managers can position their products closer to the experiential spectrum whenever possible. However, sentiment may turn negative after experiential brands respond. A potential strategy is to refocus on the tangible aspects of the support request or complaint.

The observation that high-negativity tweets receive more responses from material brands indicates that material brands actively engage with customer feedback, even when it is negative. Such visible service-recovery efforts can reduce escalation and support loyalty. Emojis are especially informative for material brands to maintain concise and resolution-focused support conversations. Timing irregularities, such as the end-of-week fatigue, expose customers to more negative experiences. Brands should pay extra attention to their social media engagement strategies by being proactive, positive, and timely to reduce latency and limit cumulative negativity. Table 6 summarises recommended actions by brand type.

Insert Table 6 about here

7. Limitations and Future Research

While our study pioneers the integration of experiential recommendation literature with sentiment analysis, it is crucial to address limitations and future research. First, longitudinal designs can track sentiment trajectories over extended periods, examining how emotional dynamics evolve across time and respond to external events. Second, our sole human validation could be complemented with alternative sentiment models to assess robustness. Third, cross-cultural research can examine whether the sentiment patterns distinguishing material and experiential brands hold across linguistic and cultural contexts, where conventions of emotion expression and emoji use may differ. Finally, context with negative emotions like anger or regret could be balanced by positive contexts such as CSR or lovemarks (Lopez *et al.,* 2020), offering a more balanced perspective beyond negative emotions.

Declaration of Competing Interest
The author declares no conflict of interest.

Funding Statement
This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Data Availability Statement
The data that support the findings of this study are available from the corresponding author upon reasonable request.
The data used in this study was collected from Twitter in 2018, prior to the 2023 policy changes implemented by X (formerly Twitter). During the time of data collection, our study fully complied with Twitter's data use and scraping policies.

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List of Tables:

Table 1. Descriptive information on the selected brands' X accounts

Brand Name	X Account Name	Number of Followers (as of the retrieval date)	Total Number of Tweets (as of the retrieval date)
Airbnb	AirbnbHelp	74.9K	345.8K
Netflix	Netflixhelps	267.6K	858.7K
Uber	Uber_Support	533.6K	1.6M
Apple	AppleSupport	1.2M	1.2M
Samsung	SamsungSupport	173.4K	525K
OnePlus	OnePlus_Support	186.3K	266.6K

Source: Authors' own work

Table 2. Summary of Tweets data

Metrics	@AirbnbHelp	@Netflixhelps	@Uber_Support	@AppleSupport	@SamsungSupport	@OnePlus_Support
Number of Tweets	SA: 5192 CA: 4808	SA: 4024 CA: 5976	SA: 5176 CA: 4824	SA: 3539 CA: 6461	SA: 5036 CA: 4964	SA: 5190 CA: 4810
Min. Tweet Length	5 (SA: 11, CA: 5)	5 (SA: 9, CA: 5)	5 (SA: 21, CA: 5)	4 (SA: 15, CA: 4)	4 (SA: 5, CA: 4)	5 (SA: 11, CA:5)
Max. Tweet Length	419 (SA: 419, CA:400)	376 (SA: 324, CA: 376)	428 (SA: 428, CA: 425)	372 (SA: 337, CA: 372)	671 (SA: 488, CA: 671)	500 (SA: 339, CA: 500)
Avg. Tweet Length	191 (SA: 228, CA:151)	128 (SA: 127, CA: 128)	148 (SA: 158, CA: 138)	153 (SA: 196, CA: 129)	164 (SA: 186, CA: 142)	135 (SA: 135, CA: 136)
Most Frequently Tweeted Day	Wed. (SA: Wed., CA: Wed.)	Wed. (SA: Mon., CA: Wed.)	Sun. (SA: Sun., CA: Sun.)	Wed. (SA: Wed., CA: Wed.)	Fri. (SA: Fri., CA: Fri.)	Wed. (SA: Wed., CA: Wed.)
Most Frequently Tweeted Hour*	14:00-14:59 (SA: 11:00-11:59, CA: 14:00-14:59)	11:00-11:59 (SA: 11:00-11:59, CA: 15:00-15:59)	11:00-11:59 (SA: 20:00-20:59, CA: 11:00-11:59)	14:00-14:59 (SA: 09:00-09:59, CA: 14:00-14:59)	16:00-16:59 (SA: 16:00-16:59, CA: 12:00-12:59)	07:00-07:59 (SA: 07:00-07:59, CA: 09:00-09:59)
Total Number of Links	2936 (SA: 2662, CA: 274)	2333 (SA: 2077, CA: 256)	524 (SA: 400, CA: 124)	2974 (SA: 2687, CA: 287)	2639 (SA: 2485, CA: 154)	1001 (SA: 667, CA: 334)
Total Number of Video	14 (SA: 0, CA: 14)	38 (SA: 0, CA: 38)	0 (SA: 0, CA: 0)	78 (SA: 3, CA: 75)	89 (SA: 40, CA: 49)	45 (SA: 1, CA: 44)
Total Number of Pictures	271 (SA: 0, CA: 271)	680 (SA: 6, CA: 674)	403 (SA: 0, CA: 403)	624 (SA: 1, CA: 623)	434 (SA: 15, CA: 419)	571 (SA: 4, CA: 567)
Total Number of GIFs	28 (SA: 0, CA: 28)	205 (SA: 60, CA: 145)	28 (SA: 0, CA: 28)	49 (SA: 0, CA: 49)	21 (SA: 2, CA: 19)	19 (SA: 0, CA: 19)
Min. Sentiment	-0.9 (SA: -0.7, CA: -0.9)	-0.9 (SA: -0.9, CA: -0.9)	-0.9 (SA: -0.8, CA: -0.9)	-0.9 (SA: -0.8, CA: -0.9)	-0.9 (SA: -0.8, CA: -0.9)	-0.9 (SA: -0.8, CA: -0.9)
Max. Sentiment	0.9 (SA: 0.9, CA: 0.9)	0.9 (SA: 0.9, CA: 0.9)	0.9 (SA: 0.8, CA: 0.9)	0.9 (SA: 0.9, CA: 0.9)	0.9 (SA: 0.9, CA: 0.9)	0.9 (SA: 0.9, CA: 0.9)
Average Sentiment	-0.05 (SA: 0.06, CA: -0.17)	-0.03 (SA: 0.08, CA: -0.10)	-0.08 (SA: 0.08, CA: -0.25)	-0.13 (SA: 0.09, CA: -0.25)	0.02 (SA: 0.27, CA: -0.24)	0.02 (SA: 0.16, CA: -0.13)

* In Eastern Standard Time (EST)

Notes: SA: Support Account, CA: Customer Account, Numbers of support accounts and customer accounts are given in parentheses.

Source: Authors' own work

Table 3. t-Test results regarding the emotional change in tweets for material vs. experiential brands

Customers tweets' sentiment of experiential vs. material brands	Welch's t-test results
Average sentiment of tweets	6.887 (p=.00)
The sentiment change from the first tweet to the second tweet	-1.932 (p=.05)
The sentiment change from the first tweet to the last tweet	-1.616 (p=.11)

Source: Authors' own work

Table 4. Tweets' engagement metrics by brand

Brands	Favourites	Retweets	Reply
Airbnb	4993	527	3574
Netflix	4478	1895	3240
Uber	1604	371	3563
Apple	4774	488	4087
Samsung	1132	280	4226
OnePlus	11925	1187	3470

Source: Authors' own work

Table 5. Coefficients of the Final Regression for Experiential and Material Brands

Coefficients	Experiential Brands	Material Brands
β_0	-0.037** (0.010)	-0.020 (0.019)
Embedded Content		
Emoji	0.117** (0.010)	0.212** (0.017)
Video	0.121* (0.045)	0.096 (0.054)
Picture	0.049** (0.009)	0.027 (0.016)
GIF	0.255** (0.023)	0.019 (0.081)
Link	0.147** (0.013)	0.014 (0.021)
Tweet Length		
[51_100]	-0.145** (0.008)	-0.136** (0.016)
[101_150]	-0.224** (0.009)	-0.202** (0.017)
[151_200]	-0.236** (0.009)	-0.202** (0.019)
[201_280]	-0.268** (0.008)	-0.230** (0.016)
Time of Posting		
Working_Hours	-0.009 (0.20)	-0.010 (0.012)
Evening	0.003 (0.020)	-0.021 (0.018)
Days		
Tuesday	0.018* (0.009)	0.058* (0.019)
Wednesday	0.026* (0.009)	0.040* (0.018)
Thursday	0.061** (0.011)	0.030 (0.020)
Friday	0.050** (0.010)	0.044* (0.020)
Saturday	0.043** (0.010)	0.030 (0.021)
Sunday	0.014 (0.009)	0.017 (0.021)

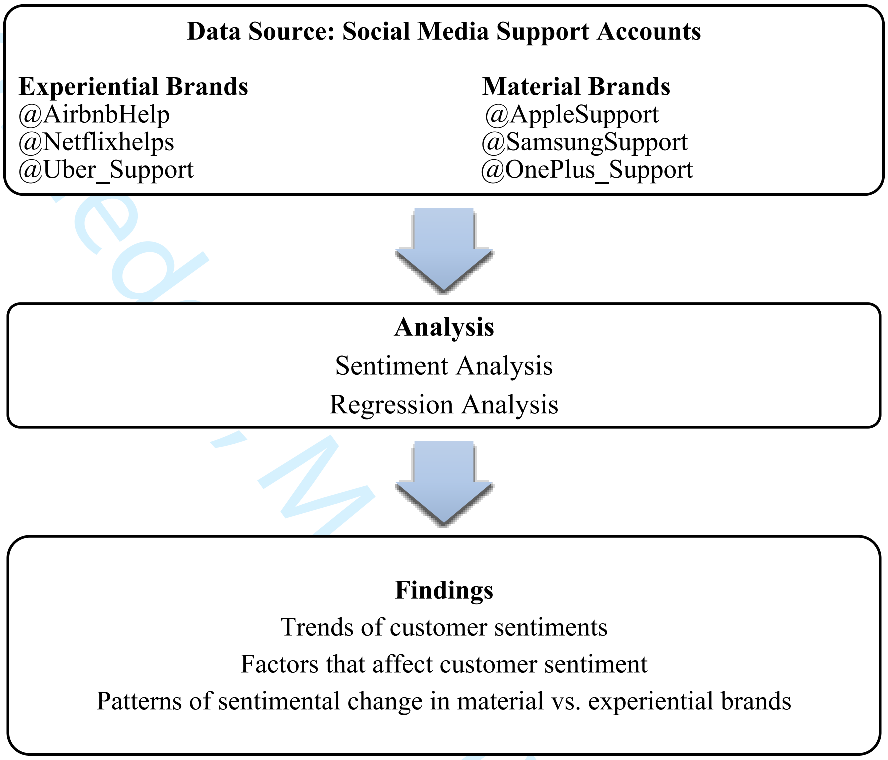
*$p < 0.05$, **$p < 0.001$.
Note: Standard errors in parentheses. Monday is the benchmark for days.
Source: Authors' own work

Table 6. Suggested actions for managers regarding online support conversations

Suggested action for managers	Suggested support account post characteristics	Suggested support account post content
Position material brands closer to the experiential spectrum	Emphasize experiential aspects in initial posts	"Our TV sets transform your living room into a theater! Enjoy an immersive experience with our latest model."
Switch focus during interactions from experiential to tangible aspects	Focus on tangible responses during extended conversations	"We understand your issue with the TV set. Let's check the connectivity options and settings to resolve it."
Engage with negative feedback actively	Be responsive to negative sentiment posts	"We're sorry to hear about your issue. Please DM us your order number and we'll make it right."
Offer around-the-clock customer support	Ensure availability during non-traditional business hours	"Having trouble late at night? Our support team is available 24/7 to assist you. Reach out anytime!"
Shorten support conversations for material brands	Keep posts concise and to the point	"Thank you for reaching out. Can you try resetting the device and let us know if it works?"

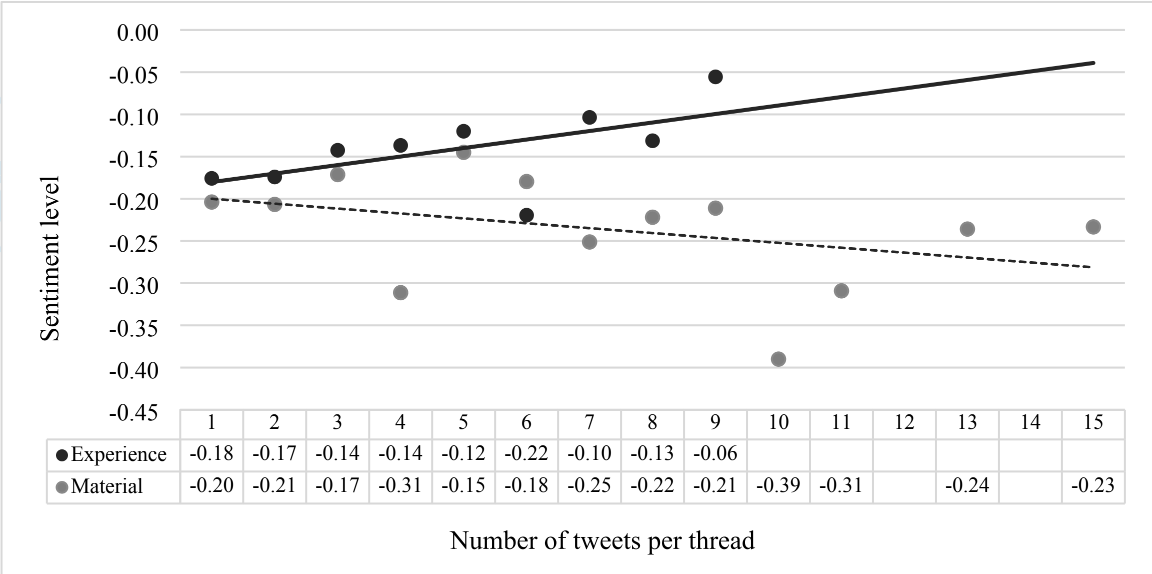
Source: Authors' own work

List of Figures:



Source: Authors' own work

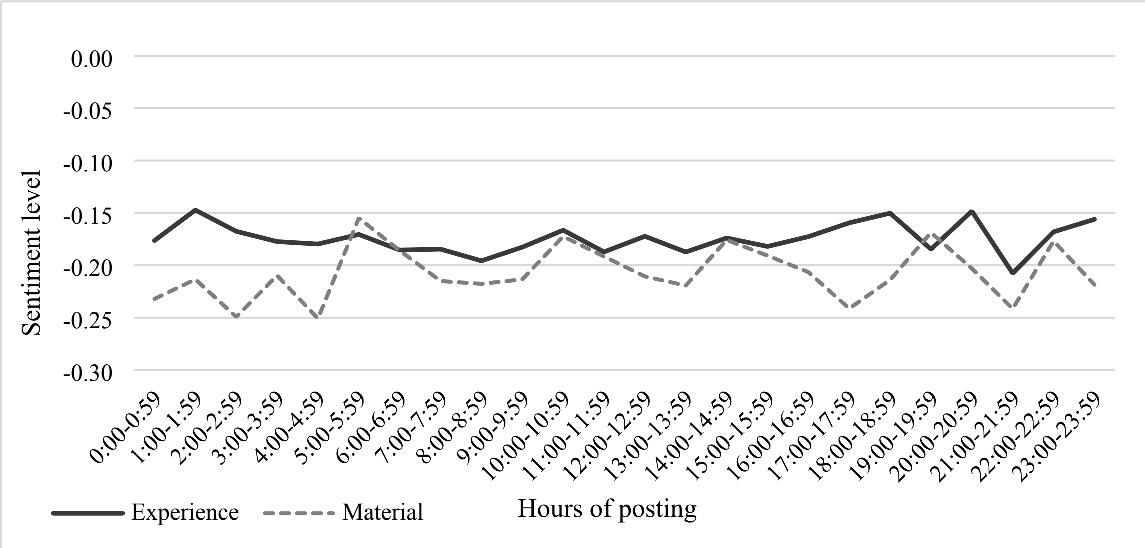
Figure 1. Research design



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
● Experience	-0.18	-0.17	-0.14	-0.14	-0.12	-0.22	-0.10	-0.13	-0.06						
● Material	-0.20	-0.21	-0.17	-0.31	-0.15	-0.18	-0.25	-0.22	-0.21	-0.39	-0.31		-0.24		-0.23

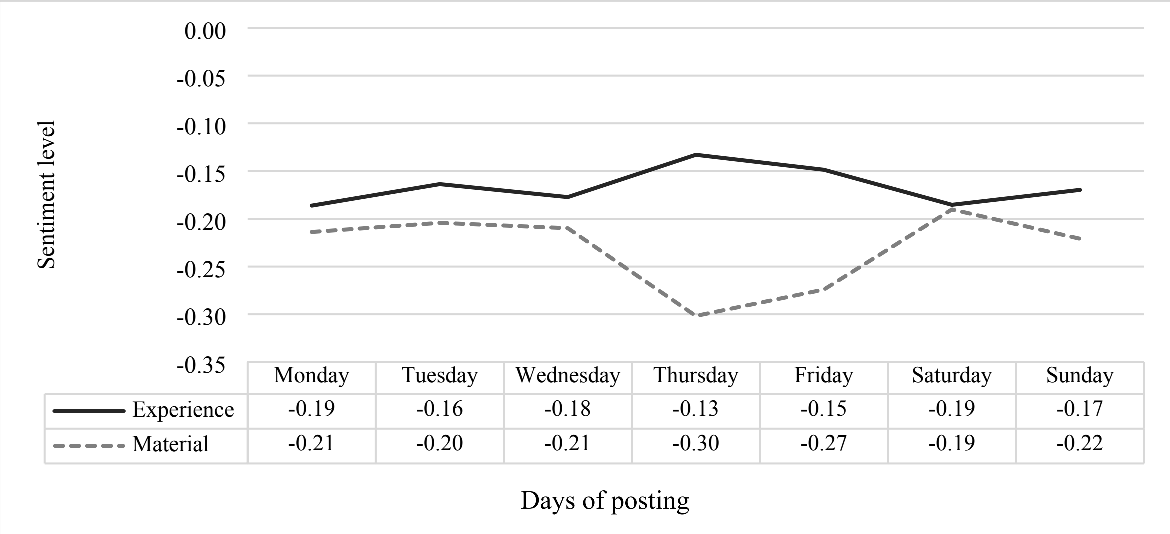
Source: Authors' own work

Figure 2. The average sentiment grouped by thread length for material vs. experiential brands



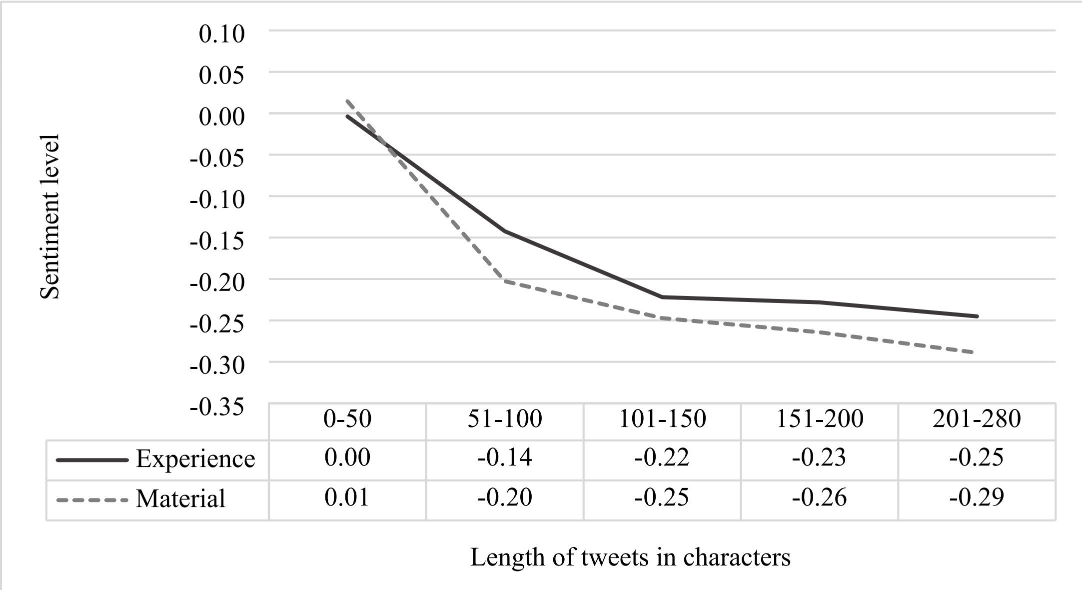
Source: Authors' own work

Figure 3. The sentiment of customers per hour (EST) for material vs. experiential brands



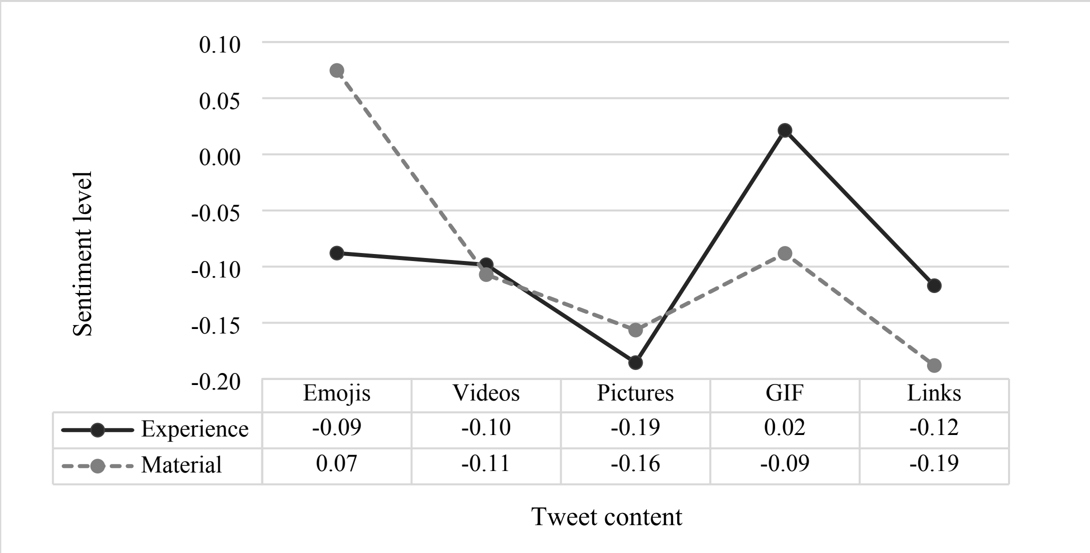
Source: Authors' own work

Figure 4. The sentiment of customers by day for material vs. experiential brands



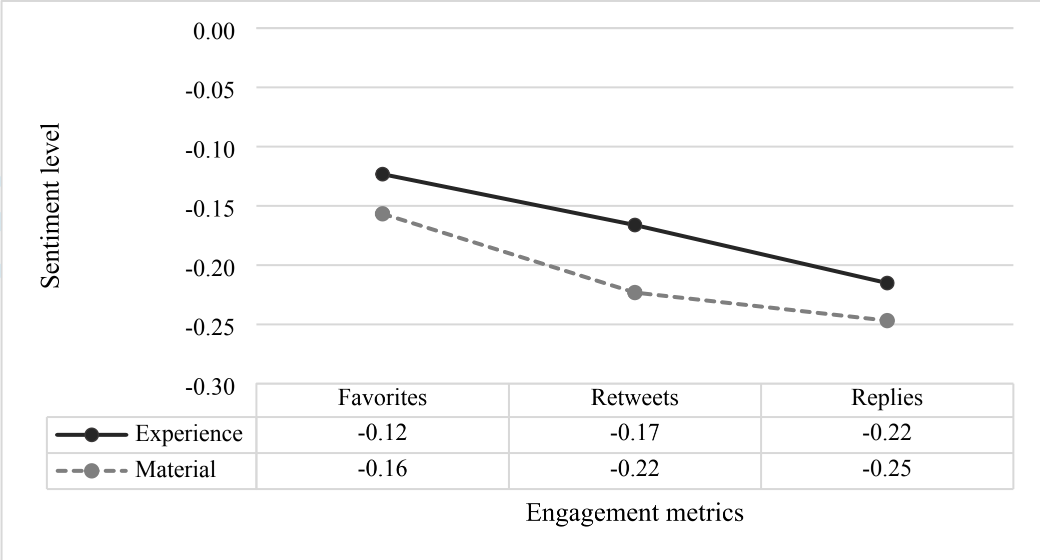
Source: Authors' own work

Figure 5. The sentiment of customers per tweet length for material vs. experiential brands



Source: Authors' own work

Figure 6. The sentiment of customers by embedded content for material vs. experiential brands



Source: Authors' own work

Figure 7. The sentiment of customers by engagement metrics for material vs. experiential brands

Supplementary Tables

Supplementary Table S1. Results of Pilot Study 1

Brands	Mean	Standard Deviation
Samsung	*2,39*	*1,685*
Samsung Galaxy	2,46	1,817
Apple iPhone	2,52	1,944
Apple MacBook	2,54	1,933
Philips	2,54	1,829
Apple	*2,64*	*2,027*
Zara	2,66	1,958
Nike	2,69	1,913
Dyson	2,84	1,660
Louis Vuitton	2,86	2,139
Microsoft	3,35	2,076
Home Depot	3,39	1,629
Activision	3,52	1,772
IBM	3,60	1,710
Oneplus	*3,67*	*1,673*
Starbucks	4,26	2,146
Subway	4,29	2,096
Mc Donald's	4,31	2,112
Walt Disney Company	4,45	2,130
KFC	4,46	2,193
Qatar Airways	4,54	1,949
Netflix	*4,61*	*2,199*
Call Of Duty	4,62	2,185
Airbnb	*5,02*	*1,861*
Uber	*5,06*	*1,888*

Source: Authors' own work

Supplementary Table S2. Results of Pilot Study 2

Brands	Mean	Standard Deviation
Samsung	3,11	2,138
Apple	3,25	2,029
Oneplus	3,52	1,849
Netflix	5,46	1,848
Airbnb	5,71	1,765
Uber	5,98	1,635

Source: Authors' own work