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Using machine learning to develop customer insights from user-generated content

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A R T I C L E I N F O

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A B S T R A C T

Uncovering customer insights (CI) is indispensable for contemporary marketing strategies. The widespread availability of user-generated content (UGC) presents a unique opportunity for firms to gain a nuanced understanding of their customers. However, the size and complexity of UGC datasets pose significant challenges for traditional market research methods, limiting their effectiveness in this context. To address this challenge, this study leverages natural language processing (NLP) and machine learning (ML) techniques to extract nuanced insights from UGC. By integrating sentiment analysis and topic modeling algorithms, we analyzed a dataset of approximately four million X posts (formerly tweets) encompassing 20 global brands across industries. The findings reveal primary brand-related emotions and identify the top 10 keywords indicative of brand-related sentiment. Using FedEx as a case study, we identify five prominent areas of customer concern: parcel tracking, small business services, the firm's comparative performance, package delivery dynamics, and customer service. Overall, this study offers a roadmap for academics to navigate the complex landscape of generating CI from UGC datasets. It thus raises pertinent practical implications, including boosting customer service, refining marketing strategies, and better understanding customer needs and preferences, thereby contributing to more effective, more responsive business strategies.

1. Introduction

Customer insights (CI), "the degree to which a firm has an understanding of current customer needs, the reasons behind these needs, and how these change over time" (Hillebrand et al., 2011, p. 595), have become a cornerstone of contemporary marketing (Berger et al., 2020; Price and Wrigley, 2016). By cultivating a deeper understanding of customer behavior and customer–firm interactions, companies can leverage CI to make strategic decisions, bolster their (financial) performance, and gain a competitive edge (Guo et al., 2020; Homburg et al., 2015; Macdonald et al., 2012).

However, despite the acknowledged importance of CI, many businesses struggle to generate such insights due to data-related and analytical limitations (Price and Wrigley, 2016; Said et al., 2015). This challenge persists because while firms increasingly recognize the value of data-driven insights, they often lack the capacity to effectively manage and interpret the vast amounts of information collected (Babić Rosario et al., 2016; Mustak et al., 2021). Furthermore, traditional

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methods of gathering CI (e.g., surveys or focus groups) can be time-consuming, expensive, and may not adequately capture customer sentiment and behavior (Liu et al., 2017).

With the rise of digital interactions, customer–firm engagement is increasingly occurring online. As individuals engage online, they leave a rich data trail, including comments, reviews, and shares, among others (Berger et al., 2020; Nilashi et al., 2021; Zaghloul et al., 2024). This user-generated content (UGC) presents a unique opportunity for marketers to glean valuable CI and gain a deeper understanding of their perceptions and behaviors (Chintagunta et al., 2016; Hollebeek and Macky, 2022; Praveen et al., 2024). However, the sheer volume and unstructured nature of user data poses a challenge to marketing academics and practitioners in extracting actionable insights from it (Balducci and Marinova, 2018; Kannan and Li, 2017). Traditional manual analytical approaches become impractical when dealing with millions of data points, such as tweets (Abu-Salih et al., 2018; Salminen et al., 2022b). Consequently, despite the immense potential of UGC for generating CI, much of its value remains untapped due to human analytical limitations, limited big data expertise, and organizational constraints (Berger et al., 2020; Manthiou et al., 2020; Mustak et al., 2021).

While traditional approaches are typically unable to handle the volume and complexity of UGC data, machine learning (ML) and natural language processing (NLP) techniques enable marketers to extract deeper, more nuanced CI, thus contributing to the firm's marketing performance (De Bruyn et al., 2020; Salminen et al., 2022b; Schaeffer and Rodriguez Sanchez, 2020). ML/NLP is already used for various strategic purposes (Abu-Salih et al., 2018; Choudhary and Arora, 2024). For example, recommender systems leverage user data to personalize product suggestions, enhancing the user experience and raising sales (Gomez-Uribe and Hunt, 2016). Similarly, demand forecasting and inventory management utilize ML to predict consumer demand patterns, thus optimizing stock levels, minimizing stockouts, and generating cost efficiencies. Moreover, streaming services, such as Netflix, further demonstrate the power of ML/NLP. By analyzing user data (e.g., browsing history), these services can recommend tailored content to users. Social media platforms like X (Twitter) also integrate ML/NLP to detect and eliminate spam, hate speech, and abusive content (IABAC, 2022).

However, despite the acknowledged potential of artificial intelligence (AI) in this domain, critical gaps exist in our understanding of how these technologies should be used to generate actionable CI from UGC. While prior research has explored marketing applications of ML/NLP, adopting these technologies to generate CI lags to date, warranting further exploration. Moreover, while understanding the application of UGC-based insight to generate CI remains limited (Rambocas and Pacheco, 2018; Salminen et al., 2022a), there is also a lack of standardized frameworks and best practices for implementing these technologies across industries. Addressing these gaps is crucial to optimizing the value of UGC data and informing the development of effective AI-driven CI practices. Accordingly, *this study explores how ML/NLP can be effectively applied to generate CI from UGC*.

To achieve this objective, we systematically gathered a dataset of over four million brand-related X posts (tweets) across five industries, each hosting four brands (Culotta and Cutler, 2016). Our analytical approach integrates ML techniques, specifically sentiment analysis and topic modeling. We first apply sentiment analysis (Rambocas and Pacheco, 2018), a text mining method, to discern and extract information from the data, helping us to understand users' social sentiment about brands, products, and services through their online dialogues (Dang et al., 2020; Gupta, 2018; Rambocas and Pacheco, 2018; Yadav and Vishwakarma, 2020). Next, we employed topic modeling, an unsupervised ML method, to uncover latent topics in the data (Jelodar et al., 2019; Nikolenko et al., 2017; Vayansky and Kumar, 2020).

Our primary focus is not to advance ML/NLP technically. Instead, we focus on using these technologies to generate CI, which remains underexplored in the literature (Berger et al., 2020; Mustak et al., 2021). This study makes two key contributions to the CI and ML/NLP literature. First, it adds to the growing corpus of research that combines AI-powered ML techniques with UGC. This approach provides novel insight, informed by big data, into established marketing concepts, such as customer response and experience (Berger et al., 2020; Roelen-Blasberg et al., 2023). Specifically, our analyses extend prior ML research in marketing by integrating sentiment analysis and topic modeling into a unified framework, thus addressing the limitations of sentiment analysis (Rambocas and Pacheco, 2018). Second, through a case study of FedEx,[1] we demonstrate how ML/NLP-based analytics can be used to understand critical marketing constructs like customers' brand preferences and emotional responses (Bass and Talarzyk, 1972; DelVecchio et al., 2006), thus raising pertinent theoretical insight and practical implications.

Next, we review the foundational literature in Section 2, followed by an overview of the adopted methodology in Section 3. We then present the findings in Section 4, followed by a discussion of their implications, limitations, and further research avenues in Section 5.

2. Conceptual Foundations

2.1. Customer insights

The online environment offers marketers a wealth of CI (Hollebeek et al., 2024; Roelen-Blasberg et al., 2022; Salminen et al., 2022b), which can be categorized into instrumental, conceptual, and symbolic insights (Macdonald et al., 2012; Said et al., 2015). Instrumental insights involve the application of knowledge to address specific business challenges or seize new opportunities, including using CI to address operational hurdles or to strengthen the firm's competitive position (Macdonald et al., 2012). Conversely, conceptual insights focus on using CI to understand customers' complex choices and behaviors (Said et al., 2015). Unlike instrumental insights, they do not require immediate action based on acquired knowledge.

Finally, symbolic insights involve using customer information to justify past actions, support ongoing activities, and inform future decisions (Bailey et al., 2009). These insights delve into the psychological and symbolic aspects of consumer behavior, thus addressing the interaction of personal experiences, perceptions, and decision-making processes. While instrumental and conceptual insights are the primary focus of most CI activities, symbolic insights offer a valuable understanding of customers' underlying motivations (Bharadwaj et al., 2013; Price and Wrigley, 2016).

Harnessing CI offers firms numerous advantages, including improved marketing decision-making, a deeper understanding of the impact of the firm's actions on consumer behavior, and more pronounced differentiation from competitors (Berger et al., 2020; Bharadwaj et al., 2013), in turn boosting marketing performance (Bailey et al., 2009; Price and Wrigley, 2016). Traditionally, businesses have relied on manual methods such as interviews, observations, focus groups, and surveys to extract CI (Schaffhausen and Kowalewski, 2015). However, these methods have limitations, particularly in the context of big data.

For example, while 1-h interviews with 20–30 participants can reveal 90–95% of users' needs or experiences (Griffin and Hauser, 1993), small sample sizes limit the generalizability and representativeness of those findings. Another challenge is the high cost incurred in implementing manual data collection and processing methods (Kühl et al., 2020; Schaffhausen and Kowalewski, 2015), which act as a double-edged sword. They hinder the widespread adoption of CI techniques and limit their scalability and the range and depth of insights.

[1] Disclaimer: Our analysis of FedEx is for academic purposes only. We aim to provide a neutral, objective assessment of how X data can be leveraged to generate customer insights. Our goal is not to criticize FedEx's operations or provide specific business recommendations.

Moreover, while organizations may lack expertise in handling traditional CI methods (Mustak et al., 2021; Salminen et al., 2022b), researcher bias can also affect manual data-analytical procedures, thus jeopardizing the validity of the findings (Hollebeek et al., 2024; Kühl et al., 2020; Schaffhausen and Kowalewski, 2015). These traditional data-analytical limitations collectively require advanced, technology-driven approaches to obtain a deeper CI.

2.2. Customer insights generated through machine-learning approaches

ML, particularly its subset of NLP applications, emerges as a useful solution for overcoming the challenges associated with manual data-analytical methods (Choudhary and Arora, 2024; Schaeffer and Rodriguez Sanchez, 2020). These powerful tools allow marketers to efficiently analyze large datasets, uncovering valuable CI (Mustak et al., 2021; Rambocas and Pacheco, 2018). Marketers can use cutting-edge ML methods to gain or sustain the firm's competitive advantage (Hartmann et al., 2019; Salminen et al., 2022a). s.

Mitchell (1997, p. 2) states, "A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E." In this vein, ML algorithms excel at uncovering data patterns, given their capacity to learn and adapt autonomously through iteration without human intervention (Hollebeek et al., 2021), allowing them to identify complex relationships in large datasets (Choudhary and Arora, 2024; Mohri et al., 2018; Shalev-Shwartz and Ben-David, 2014). By harnessing ML, marketers can extract valuable CI by segmenting audiences based on their preferences, predicting needs and behaviors, and influencing consumer decision-making processes (Cui et al., 2006; Hollebeek et al., 2024).

In this study, the generation of CI involves the simultaneous deployment of two complementary algorithm types: sentiment analysis and topic modeling (Rambocas and Pacheco, 2018; Vayansky and Kumar, 2020). Sentiment, as defined by the Oxford English Dictionary, pertains to an individual's feelings related to an object (OED Online, 2022). Accordingly, in our study, sentiment analysis encompasses the identification (nature), quantification (intensity), and comprehension (motivations) of customers' emotions toward a brand or firm (Cheng and Huang, 2020; Piryani et al., 2017). By leveraging NLP techniques, sentiment analysis automates the process of analyzing vast amounts of (e.g., textual, speech) data, which would be extremely laborious and time-consuming if done manually (Chowdhary, 2020; Kumar et al., 2023; Nilashi et al., 2021).

Classification, a pivotal ML component, allows algorithms to assign observations automatically to specific classes or groups (Kotsiantis et al., 2007; Yiu, 2019). For example, email-based spam detection represents a binary classification task (i.e., spam or non-spam). Similarly, ML can be applied to classify the price of a San Francisco apartment based on specific factors (Salian, 2018). Using similar principles, NLP algorithms in sentiment analysis automatically classify text based on its positive, negative, or neutral valence (Liu et al., 2017). Algorithms can also classify textual data based on objectivity (vs. subjectivity), offering nuanced insights into belief, joy, or trust-based UGC data (Dang et al., 2020; Rambocas and Pacheco, 2018).

Complementing sentiment analysis, we utilized topic modeling to extract topics (themes) from textual data (Berger et al., 2020; Hannigan et al., 2019). Essentially, topic models utilize textual data inputs to generate interpretable topics, while estimating the strength of these topics in the data (DiMaggio et al., 2013). Analogous to factor analysis that uncovers underlying factors, topic modeling unveils "hidden" topics in a textual corpus (Berger et al., 2020). To extract beyond-sentiment CI, we leverage Latent Dirichlet allocation (LDA), a specific topic modeling algorithm (Jelodar et al., 2019; Zhang et al., 2021) that has demonstrated efficacy across contexts, including assessment of customer complaints, service quality, and competing products (Jelodar et al., 2019; Korfiatis et al., 2019). By deploying LDA, we can pinpoint core customer topics, text-based themes, and key terms, helping us understand customer sentiment. ML permits the prediction of customers' needs or behavior, revealing its parallel usefulness in generating CI. Firms that adhere to regulations, such as the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA), can build customer trust while protecting sensitive information (Voigt and Von Dem Bussche, 2017).

Algorithmic fairness and bias represent further potential concerns. While companies like Google and IBM are developing techniques to detect and reduce bias (Bellamy et al., 2018), IBM's "AI Fairness 360 Toolkit" helps detect and mitigate bias in ML models, promoting equitable outcomes (Bellamy et al., 2018). Moreover, promoting the interpretability of complex models through explainable AI enhances transparency and trust in the attained insight (Doshi-Velez and Kim, 2017). ML can also be used to raise ethical data management standards. In this vein, companies are pioneering frameworks for data privacy and responsible AI use, setting industry benchmarks. Implementing robust data protection safeguards customer privacy and strengthens consumer trust and loyalty (Voigt and Von Dem Bussche, 2017). By prioritizing AI transparency, data security, and ethics, firms can leverage ML to generate unbiased, accurate CI.

3. Methodology

3.1. Data collection

3.1.1. Research context

We use X (formerly Twitter) to generate CI due to its widespread use for sharing brand experiences, expectations, and opinions (Chahine and Malhotra, 2018). X discussions consist of posts (tweets), brief maximum 280-character communications known for their diversity, dynamism, and colloquial nature (Ghiassi et al., 2016). With extensive UGC and the active participation of consumers and firms (Roma and Aloini, 2019), X presents an ideal platform for extracting CI (Culotta and Cutler, 2016). It also offers a cost-effective means to engage with large audiences, explaining why nearly every "Fortune Global 2000" company maintains an X account.

Many companies, therefore, leverage X to generate CI. For example, Netflix uses the platform to gauge viewers' responses to new releases, identifying trends and preferences to inform its content production and marketing strategies (Gomez-Uribe and Hunt, 2016). Similarly, Delta Airlines employs X (Tweeter) to monitor customer feedback in real time, enabling it to address service issues and raise customer satisfaction promptly (Stieglitz et al., 2018). Starbucks also uses X to engage with customers and gather feedback on its new products, helping them refine their offerings and enhance the customer experience.

At the same time, we use X to generate CI for several reasons. First, most content on X is publicly accessible through its Application Programming Interface (API), with only protected accounts (around 10%) exceptions. Second, Twitter's API empowers researchers to collect focused data through queries. For instance, one can retrieve posts on a specific topic in the last 20 min or gather users' retweets, thus allowing us to collect relevant, timely data.

3.1.2. Brand selection

We adopted Liu et al.'s (2017) procedure to determine our focal brands. Initially, we identified five sectors with heightened customer attention, aligning with the Global Industry Classification Standard (GICS), including consumer services, food & beverage, retailing, apparel & footwear, and consumer electronics. In each industry, we selected four representative "Fortune Global 2000" brands, yielding a set of 20 global brands for further analysis (see Table 1).

To ensure transparency and credibility, we selected brands in each sector based on key criteria. First, we considered each brand's market share and global reach, ensuring its significant presence and influence in its respective sectors. Second, we assessed brand activity and

Table 1
Studied sectors and brands.

	Sector				
	Consumer Services	Food & Beverage	Retailing	Apparel & Footwear	Consumer Electronics
Brands	FedEx	Coca-Cola	Amazon	Adidas	Fitbit
	Marriott	McDonald's	Macy's	Gap	Nintendo
	Netflix	Nestle	Tesco	Nike	Samsung
	Uber	Starbucks	Walmart	Puma	Sony

engagement on X, given the key role of active participation in UGC (Hollebeek and Macky, 2022). Finally, we considered the diversity of the brands to ensure that we captured a broad range of customer experiences and sentiments.

The rationale for choosing "Fortune Global 2000" brands lies in their respective established market position and extensive customer base, offering a rich source for data analysis. These brands will likely generate substantial online interactions, permitting an in-depth assessment of customer perceptions and behaviors. Moreover, by focusing on prominent brands with significant digital footprints, we aimed to enhance the relevance and generalizability of our findings.

3.1.3. Data extraction from X (Twitter)

To systematically collect brand-related posts, we employed a combination of X's API and custom web crawling algorithms coded in Python. Data were collected in 2022–2023 before Twitter was rebranded as X. The initiation of a developer account on the Twitter applications website is a prerequisite for accessing Twitter's API (Owe, 2020; Sistilli, 2022). We used Tweepy as the Twitter API client (see Fig. 1) to conduct our analyses. In X communications, "@" precedes usernames to deliver tweets to users. Accordingly, we used the hashtag "@company" to aggregate tweets for the chosen brands. Our data harvesting efforts resulted in the extraction of approximately 200,000 posts per brand, culminating in 4 million posts (excluding reposts).

We extracted specific variables (e.g., tweet content, timestamp, and user handle) from the tweets to enrich our analysis. We also captured metadata, including tweet language and hashtags, allowing us to perform a detailed analysis.

3.2. Data analysis

3.2.1. Data preprocessing

Before analyzing the data, we conducted a preprocessing phase to comply with established procedures (Berger et al., 2020; Bonthu, 2021) using our primary input (tweets). This comprises natural, informal, and colloquial language, often accompanied by extraneous information (e.g., account names, likes, or retweets). The stepwise procedures shown in Table 2 (Bonthu, 2021) summarize our analytical approach to refine and prepare the data for subsequent analysis.

During data cleaning, we distinguished between meaningful and irrelevant hashtags. Careful filtering ensured that only relevant information was retained. Tokenization, which breaks down text into individual units, occasionally fragmented compound words. To address this, we used a custom preprocessing step with a dictionary-based approach to preserve compound words. We also removed noise and standardized the text. This ensured that our models were trained with clean, representative data. As a result, the reliability, robustness, and accuracy of our sentiment analysis and topic modeling were enhanced.

```
Text = "I like this new show on Netflix very much"

Tokens = word_tokenize(text)

tokens

['I', 'like,' 'this', 'new', 'show', 'on', 'Netflix', 'very', 'much',]
```

Fig. 2. Example of NLP-based tokenization.

3.2.2. Sentiment analysis

In this phase, we employed rule-based Python libraries to gain insight into customer sentiment, specifically utilizing a lexicon-based sentiment analysis approach (Jurek et al., 2015; Taboada et al., 2011). This method involves assessing sentiment orientation by examining the semantic alignment of words or phrases in the data and assigning a score to documents based on the cumulative sentiment scores of the words it incorporates. The sentiment lexicon employed in this analysis attributes sentiment scores to individual words, exemplified in Fig. 4, by applying Python-based Valence Aware Dictionary and Sentiment Reasoner (VADER). VADER, as a rule-based lexicon and sentiment analysis tool tailored to social media sentiments, plays a pivotal role in evaluating the emotional tone of textual content.

To supplement the sentiment analysis results, we found that VADER allowed us to capture the emotional tone of customer feedback. Specifically, it provided detailed sentiment scores aggregated to identify overall trends. For example, positive, negative, and neutral sentiments were quantified separately. We also classified sentiments, revealing key insights into consumer attitudes toward the studied brands.

3.2.3. Topic modeling

We employed topic modeling to attain a more nuanced understanding of the data. We first delineated the desired level of insight, ranging from aggregate-to industry-specific, individual-or firm-level insight (Mustak et al., 2021). Opting for firm-level analysis, we discerned pivotal firm issues articulated by its clientele. By focusing on FedEx tweets, we sought to uncover reasons for the prevalence of customers' negative brand-related sentiment (Hollebeek and Chen, 2014). The principles and algorithms guiding this analysis are generalizable to other brands. The variance in application primarily lies in the dataset used to feed the algorithms (e.g., to reveal latent "food & beverage"

```
import os
import sys
from tweepy import API
from tweepy import OAuthHandlerdef get_twitter_auth():
#set up twitter authentication# Return: tweepy.OAuthHandler objecttry:
consumer_key = os.environ['TWITTER_CONSUMER_KEY']
consumer_secret = os.environ['TWITTER_CONSUMER_SECRET']
access_token = os.environ['TWITTER_ACCESS_TOKEN']
access_secret= os.environ['TWITTER_ACCESS_SECRET']
except KeyError:
sys.stderr.write("TWITTER_* environment variables not set\n")
sys.exit(1)
auth = OAuthHandler(consumer_key, consumer_secret)
auth.set_access_token(access_token, access_secret)
return authdef get_twitter_client():
#Setup twitter API client.# Return tweepy.API objectauth = get_twitter_auth()
client = API(auth)
return client
```

Fig. 1. Illustration – Establishment of Twitter client for data collection. Source: Owe (2020).

```
print(stopwords.words('english'))
```

```
['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "you're", "you've", "you'll", "you'd", 'your', 'yours',
'yourself', 'yourselves', 'he', 'him', 'his', 'himself', 'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'its
elf', 'they', 'them', 'their', 'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "that'll", 'these',
'those', 'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'had', 'having', 'do', 'does', 'did', 'doin
g', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as', 'until', 'while', 'of', 'at', 'by', 'for', 'with', 'about',
'against', 'between', 'into', 'through', 'during', 'before', 'after', 'above', 'below', 'to', 'from', 'up', 'down', 'in', 'o
ut', 'on', 'off', 'over', 'under', 'again', 'further', 'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'al
l', 'any', 'both', 'each', 'few', 'more', 'most', 'other', 'some', 'such', 'no', 'nor', 'not', 'only', 'own', 'same', 'so',
'than', 'too', 'very', 's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'now', 'd', 'll', 'm', 'o',
're', 've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't", 'doesn', "doesn't", 'hadn', "hadn't", 'has
n', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mightn', "mightn't", 'mustn', "mustn't", 'needn', "needn't", 'sha
n', "shan't", 'shouldn', "shouldn't", 'wasn', "wasn't", 'weren', "weren't", 'won', "won't", 'wouldn', "wouldn't"]
```

Fig. 3. Example of English stopwords used in NLP.

Table 2
Stepwise data preprocessing approach.

Step 1: Data cleaning	We removed redundant white space characters, non-alphabetic characters, and stopwords—words devoid of substantial meaning in the text (e.g., "@," "and," "the," or "or"). The cleaning function was applied to the primary texts, resulting in refined text devoid of these specified elements.
Step 2: Tokenization	Tokenization involves breaking the text into smaller units (i.e., tokens). Our approach primarily adopted word-level tokenization, facilitated by the nltk tokenize function word_tokenize (Bonthu, 2021). For example, the tweet "I like this new Netflix show very much" would be dissected into individual fragments or tokens, as shown in Fig. 2.
Step 3: POS tagging	Part of speech (POS) tagging entails assigning a tag to each token based on its POS. This step is crucial for maintaining word context and enabling lemmatization. Leveraging the nltk pos_tag function, we tagged each token to create tuples in the form (word, tag).
Step 4: Stopword removal	Stopwords conveying minimal meaningful information in English were eliminated during text preprocessing. The nltk library supplied a list of widely used stopwords in English (see Fig. 3).
Step 5: Obtaining stem words (Lemmatization)	The final preprocessing stage involved lemmatization, wherein pos tag tuples were processed to derive each word's lemma (canonical form or dictionary form), thus enhancing the textual data's consistency and interpretability.

topics, one would input the corresponding data for this sector).

Following Nikolenko et al. (2017), we applied a structured workflow based on the LDA algorithm to conduct topic modeling (Pravakaran, 2018). The assemblage of D tweets is assumed to contain T topics expressed through W different words. Each tweet $d \in D$ of length N_d is modeled as a discrete distribution (d) over the set of topics $(zj = t) = (d)$, where z is a discrete variable that defines the topic for each word instance $j \in d$. Each topic, in turn, corresponds to a multinomial word-related distribution, $p(w|z_j = t) = \phi_w^{(t)}$. The Dirichlet priors α can be assigned to the distribution of topic vectors $\boldsymbol{\theta}$, $\boldsymbol{\theta} \sim \mathrm{Dir}(\boldsymbol{\alpha})$, similar to $\boldsymbol{\beta}$ for the distributions of words in topics, $\varphi \sim \mathrm{Dir}(\boldsymbol{\beta})$. To develop and deploy the algorithm, we used the Python programming language (Version 3.9) and the Jupyter Notebook (Update, 2021) platform to generate the visual illustration. With the gensim library's native LdaModel, we generated meaningful topics and created visualizations using the matplotlib library.

When preprocessing the data, we constructed word bigrams to represent composite terms (e.g., by linking "big" and "data" as "big _ data"). Employing algorithms, we also lemmatized each word to its root form (e.g., by transforming "approaching" to "approach; " prakharr0y, 2020). Subsequently, using the LdaModel library, we generated both the corpus and the dictionary. Rather than arbitrarily selecting a predetermined number of topics, our approach involved determining the optimal number of topics inherent in the data. Our analyses identified five topics (themes) that most effectively encapsulate the pivotal rationales underlying customers' FedEx sentiments. Fig. 5 provides a snippet of the code, while Fig. 6 visually illustrates the optimum number of topics.

Concluding the analysis, we identified five main themes of customers' sentiments toward FedEx (see Fig. 7), summarizing the multifaceted aspects of customer perceptions and emotions toward the brand.

4. Findings

4.1. Sentiment analysis

4.1.1. Text classification

The initial step to gauge customers' brand-related sentiment involves discerning the "polarity of the text" (Bonthu, 2021; Jurek et al., 2015; Piryani et al., 2017). We classified each tweet as positive, neutral, or negative, followed by a tally of the cumulative counts for each sentiment category for each brand, allowing us to compute the percentage of positive, negative, and neutral tweets (see Table 3).

Each tweet's sentiment orientation was evaluated by examining the semantic alignment of its words and phrases, assigning cumulative sentiment scores to classify the tweets. Each tweet received a cumulative sentiment score classified as positive, negative, or neutral. For example, positive tweets might say, "I love the new features on my Samsung phone." Words like "love" and "new features" carry positive connotations, contributing to a high sentiment score. Conversely, negative tweets like "I'm disappointed with the service at FedEx" would receive a low score. This approach allowed us to quantify and analyze the overall sentiment distribution across the chosen sectors and brands.

Sentiment analysis revealed interesting variations across industries. The apparel & footwear sector boasted the highest average proportion of positive sentiment (58.32%), followed by food & beverage (52.77%) and retailing (48.75%). Conversely, consumer electronics (31.54%) and consumer services (37.04%) displayed the lowest share of positive sentiment. However, consumer electronics also featured the lowest proportion of negative sentiment (12.93%), with a significant portion of customers (55.5%) expressing neutral sentiments toward it. Negative sentiment increased incrementally from electronics to apparel &

```
a = 'The new Nike shoes are nice.'
sid.polarity_scores(a)
OUTPUT-{'neg': 0.0, 'neu': 0.527, 'pos': 0.446, 'compound': 0.429}
a = 'This is the best pair of sneakers ever from Nike!! '
sid.polarity_scores(a)
OUTPUT-{'neg': 0.0, 'neu': 0.324, 'pos': 0.682, 'compound': 0.8548}
```

Fig. 4. Example: Sentiment analysis using Python-based VADER.

```python
# Show graph


topics_list = [1, 5, 6, 7, 8, 9, 10, 15]
plt.plot(topics_list, coherence_values)
plt.xlabel("Num Topics")
plt.ylabel("Coherence score")
plt.legend(("coherence_values"), loc='best')
plt.show()
```

Fig. 5. Sample code to identify the optimum number of topics.

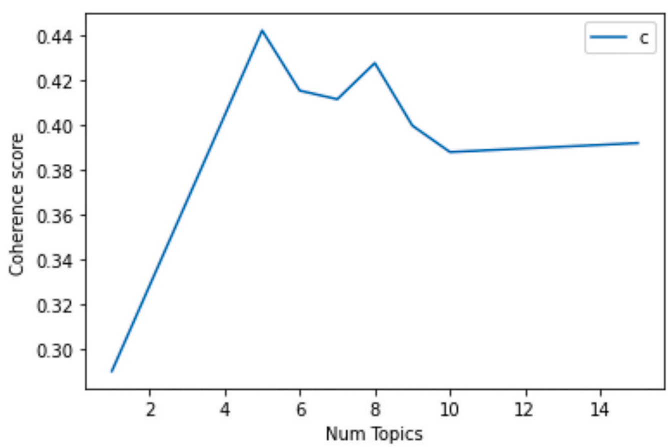

Fig. 6. Optimum number of topics that best capture the latent topics.

footwear (14.73%), food & beverage (17.7%), consumer services (19.13%), and retail sales (22.1%).

We also subtracted the percentage of negative sentiment from the positive sentiment to gain a more nuanced understanding of customers' overall sentiment, thus permitting insight into the net positivity of sector- and brand-related sentiment. This allowed us to move beyond a basic positive vs. negative classification to delve deeper into sentiment dynamics. Examining these patterns, we observed significant sentiment variations across the studied brands in the same sector, highlighting the intricate nuance that shapes consumers' brand perceptions and preferences.

The analysis also revealed significant within-sector variations in customer sentiment. For example, in consumer services, Marriott led with the highest positive sentiment share (45.7%), indicating a broadly favorable disposition toward the brand among its clientele. Conversely, Netflix received the lowest positive sentiment score (30.38%), suggesting its customers' lower enthusiasm than other brands in this sector. Interestingly, Marriott's customers not only expressed the lowest negative sentiment (9.6%) but exhibited a considerable neutral sentiment (44.6%), suggesting its more balanced brand perception than others in the sector.

On the other hand, FedEx presented an interesting contrast. While securing the second highest positive sentiment score in the consumer services sector (39.1%), it also garnered the highest share of negative sentiments. This intriguing finding implies that FedEx's customer base tends to hold more pronounced and polarized brand opinions than other players. Supporting this observation, FedEx customers displayed the lowest neutrality percentage (36%), suggesting a higher propensity to express strong positive or negative brand-related sentiment than their sector counterparts.

The sentiment analysis findings have important implications for firms, as they reveal how consumers perceive and engage with brands across sectors (Hollebeek and Chen, 2014). For example, the higher positive sentiment in the consumer electronics and apparel & footwear sectors suggests high customer satisfaction and loyalty. Conversely, the higher negative sentiment observed for brands like FedEx highlights areas for improving the customer experience. Firms can thus leverage the attained insight to tailor their marketing strategy, enhance customer service, and address specific pain points along the customer journey (Hollebeek et al., 2023), boosting their performance. By understanding the landscape of nuanced sentiment, companies can make informed decisions to strengthen the reputation and competitive advantage of their brand(s).

4.1.2. *Sentiment classification*

Our analyses extended beyond-sentiment polarity (i.e., positive, negative, neutral) to incorporate customers' emotion detection (e.g., joy, frustration, rage, or sadness) (Sentiment Analysis: A Definitive Guide, 2022). For instance, tweets might express positive emotions such as:

- "Netflix has the best selection of movies!" (Joy)
- "Hulu has a great user interface." (Satisfaction)

Conversely, tweets may also reflect negative emotions, including the following:

- "I dislike the new crime series on Netflix." (Disappointment)
- "I hate waiting for the next [season] of a series to come out on Netflix." (Frustration)

```python
# display all topics with weight of all keywords
for i,topic in best_model.show_topics(formatted=True, num_topics=best_topic_number, num_words=10):
    print(str(i)+": "+ topic)
    print()
```

Fig. 7. Illustration - Modeled salient topics.

Table 3
Primary emotion classification from tweets.

Sector	Brand	Text Classification			*Differences*
		Positive	Negative	Neutral	
Consumer Services	FedEx	39.1	24.9	36	14.2
	Marriott	45.7	9.6	44.6	36.1
	Netflix	33	19.8	47.11	13.2
	Uber	30.38	22.23	47.37	8.15
Sector Average		37.04	19.13	43.77	17.91
Apparel & Footwear	Coca-Cola	61.1	15.1	23.8	46
	McDonald's	47.1	22.5	30.4	24.6
	Nestle	57.7	15.9	26.4	41.8
	Starbucks	45.2	17.3	37.5	27.9
Sector Average		52.77	17.7	29.52	35.07
Retailing	Amazon	66.9	14.8	18.3	52.1
	Macy's	44.8	15.2	40	29.6
	Tesco	44.3	33.3	22.4	11
	Walmart	39	25.1	35.9	13.9
Sector Average		48.75	22.1	29.15	26.65
Apparel & Footwear	Adidas	63.30	10.30	26.00	53.00
	Gap	39.90	20.60	39.60	19.3
	Nike	63.20	13.20	23.60	50
	Puma	66.90	14.80	18.30	52.10
Sector Average		58.33	14.73	26.88	31.45
Consumer Electronics	Fitbit	31.15	9.2	59.6	21.95
	Nintendo	38.75	15.57	45.67	23.18
	Samsung	26.52	11.23	62.23	15.29
	Sony	29.75	15.71	54.5	14.04
Sector Average		31.54	12.92	55.5	18.61

By analyzing these emotions, companies can gain valuable CI. Interestingly, Table 4 reveals that across all sectors, a significant portion of customers express brand-related "anticipation," followed closely by expressions of "trust." Zooming in on individual brands in Table 4, we see Gap leading the apparel & footwear sector in terms of trust (46.2%), surpassing other brands in this category. Similarly, Sony stands out in the consumer electronics sector with the highest customer trust score (39.21%).

We find that established global brands generally receive positive sentiment. However, there is room for improvement. Table 4 reveals negative customer emotions across all sectors and brands. These emotions include anger, disgust, sadness, and fear, highlighting the importance of firms identifying the root causes of negative sentiment and taking action to minimize its occurrence and improve brand perception.

Sentiment analysis extends beyond simply analyzing the positivity or negativity of individual words. Emotions are often conveyed implicitly. For example, statements like "Another Monday and another week of work" might express frustration without using any overtly negative words. This challenges sentiment analysis algorithms that rely on NLP techniques to capture these implicit emotional nuances. To advance our understanding, further analyses based on large-scale big data are imperative. Advanced ML algorithms enable the processing of natural language, allowing the identification of the most common words associated with individuals' expressed emotions.

Applying this approach to the sampled four million tweets, we unveil the top 10 terms reflecting customers' positive and negative brand-related emotions, presented in Tables 5 and 6, respectively. For instance, to express positive emotions, Marriott hotel customers frequently use terms like "reward" and "grand," shedding light on specific aspects of their brand appreciation. Similarly, Amazon buyers employ terms like "top" and "support," while Sony customers mention terms such as "entertain[ing]" and "cool," revealing the distinctive strengths of these brands. Notably, when articulating positive brand-related emotions, customers tend to rely on a limited vocabulary, likely influenced by Twitter's 280-character limitation. Consequently, terms like "like/liking," "good," "love," or "thank" consistently represent customers' positive brand-related emotions.

Furthermore, understanding customers' negative brand-related emotions is of value to brands, as it points out areas for improvement. Our application of ML algorithms facilitates the identification of customers' most frequently used terms to express their negative brand-related sentiments (see Table 6). A closer examination of these words unveils intriguing insights. For example, in the case of FedEx (consumer service), customers frequently employ words like "suck," "problem," or "fail" to convey their negative sentiment. In food & beverage, McDonald's is commonly associated with terms like "fat," "die/dying," or "disappoint[ment]." At the same time, the retailing giant Tesco is widely linked to sentiments such as "bad," "cheap," or "hate."

While social media may amplify negative brand emotions, jeopardizing its reputation (Beck et al., 2023), it also offers opportunities to improve consumer perceptions. For example, while negative sentiments that go viral may damage a firm's reputation, its prompt, effective responses to negative UGC can turn the tide (Salminen et al., 2022b). Therefore, firms that actively monitor social media discussions, empathetically address consumer concerns, and offer timely solutions can mitigate the damage and end up with more satisfied or loyal customers (Beck et al., 2023; Brandes et al., 2022). Moreover, social media can be used to personalize customers' brand interactions and offer (hyper)targeted marketing activities, which are also likely to raise brand perceptions and attitudes (Balducci and Marinova, 2018; Berger et al., 2020; Hollebeek et al., 2021). However, on the downside, social media

Table 4
Customer emotions for the studied brands.

Sector	Brand	Anger	Disgust	Sadness	Fear	Anticipation	Trust	Surprise	Joy
Consumer Services	FedEx	2.12	0.7	0.6	3.45	56.6	32.2	3.91	0.31
	Marriott	2.46	0.85	1.17	4.33	45.4	28.7	5.88	11
	Netflix	1.38	0.33	1.81	3.04	67.5	21.22	4.5	0.15
	Uber	4.88	1.38	1.62	5.79	46.93	30.69	8.09	0.59
Food & Beverage	Coca-Cola	6.27	2.09	2.02	5.83	42.5	32.1	7.9	1.1
	McDonald's	5.29	3.3	1.37	14.1	45.9	21.65	7.85	0.39
	Nestle	7.5	1.94	2.93	7.37	39.8	32.8	7	0.45
	Starbucks	7.3	1.5	2.22	5.6	53.2	21.6	7.47	0.8
Retailing	Amazon	3.87	1.5	2.57	12.3	44.7	27.66	6.83	0.4
	Macy's	3.11	1.2	1.88	4.09	48	26.9	13.9	0.72
	Tesco	3.83	1.5	1.7	8.4	49.3	27.8	6.87	0.3
	Walmart	3.99	2.45	1.99	8.9	46.5	23.8	11.23	1.06
Apparel & Footwear	Adidas	3.39	1.79	7.55	18.15	37.87	27.42	3.52	0.27
	Gap	2.32	1.76	2.33	4.47	36.41	46.20	6.30	0.16
	Nike	6.68	1.57	8.47	10.14	46.64	21.63	4.32	0.50
	Puma	0.59	0.21	0.65	90.96	3.58	2.60	1.35	0.03
Consumer Electronics	Fitbit	1.67	0.67	1.83	2.24	62.8	27.1	3.3	0.19
	Nintendo	4.02	1.51	4.88	8.81	42.56	33.24	4.63	0.33
	Samsung	3.78	2.26	5.22	5.12	42.5	37.29	3.63	0.17
	Sony	2.7	1.67	2.83	5.1	43.8	39.21	4.27	0.29

Table 5
Top 10 terms reflecting customers' positive brand-related emotions.

Sector	Brand	1	2	3	4	5	6	7	8	9	10
Consumer Services	FedEx	like	work	thank	good	Right	win	love	free	best	well
	Marriott	thank	love	like	reward	Work	great	good	grand	nice	enjoy
	Netflix	good	love	work	thank	better	commend	wonder	enjoy	hot	win
	Uber	free	love	work	cool	Well	super	great	better	best	support
Food & Beverage	Coca-Cola	like	thank	love	good	Great	favor	enjoy	work	best	better
	McDonald's	like	love	work	good	Thank	right	free	better	well	best
	Nestle	like	good	free	right	Pure	work	win	love	thank	hot
	Starbucks	like	love	work	free	Good	right	thank	best	better	hot
Retailing	Amazon	win	free	love	work	Great	well	top	better	support	hot
	Macy's	like	thank	love	work	Win	good	free	great	right	well
	Tesco	like	thank	work	good	Love	well	great	best	right	free
	Walmart	like	work	winning	good	Love	night	thank	free	best	better
Apparel & Footwear	Adidas	boost	like	love	good	Top	free	best	fav	win	thank
	Gap	like	work	good	love	Right	skill	well	better	great	top
	Nike	like	love	free	good	Work	best	thank	right	top	great
	Puma	like	love	grand	protect	Good	top	support	favor	super	thank
Consumer Electronics	Fitbit	great	smart	best	better	Free	right	cool	top	worth	wonder
	Nintendo	super	like	win	love	Best	good	fun	classic	support	hero
	Samsung	smart	led	win	free	Work	better	top	great	thank	grand
	Sony	good	free	love	right	Win	entertain	support	super	smart	cool

Table 6
Top 10 terms reflecting customers' negative brand-related emotions.

Industry	Brand	1	2	3	4	5	6	7	8	9	10
Consumer Services	FedEx	plea	miss	Hate	damn	worst	wrong	bad	suck	problem	fail
	Marriott	plea	miss	Break	concern	fall	breach	hang	wrong	disappoint	cheap
	Netflix	chill	plea	Bad	dead	miss	hate	damn	bore	addict	stranger
	Uber	die	miss	Bad	bore	sin	hard	wrong	error	kill	drunk
Food and Beverage	Coca-Cola	sin	plea	Pan	wrong	die	bad	cold	miss	limit	hate
	McDonald's	plea	miss	Shake	fat	die	wrong	hard	break	disappoint	cold
	Nestle	toll	die	Lech	boycott	plea	drought	break	steal	bad	kill
	Starbucks	plea	miss	Cold	bad	hate	addict	wrong	fall	sad	suck
Retailing	Amazon	die	bad	Break	kill	problem	hard	limit	cheap	lost	wrong
	Macy's	plea	miss	Damn	bad	fall	smell	lost	disappoint	suck	hell
	Tesco	plea	miss	Bad	wrong	disappoint	cheap	hard	lost	hate	risk
	Walmart	hate	plea	Damn	bad	murder	hell	miss	kill	steal	inflict
Apparel & Footwear	Adidas	flirt	plea	Limit	sin	bad	hard	damn	seud	miss	hate
	Gap	plea	miss	Poor	problem	hard	fall	hate	wrong	break	lose
	Nike	crush	plea	Damn	cheap	bad	hate	limit	tout	hard	dope
	Puma	wild	sin	Seud	pinch	plea	shit	barbarian	miss	die	jam
Electronics	Fitbit	burn	lost	Die	fat	problem	bad	miss	fall	break	broker
	Nintendo	smash	plea	Bad	die	limit	monster	rumor	blow	hack	leak
	Samsung	hard	leak	Problem	bad	cheap	rumor	crack	tout	cloud	fail
	Sony	bad	hard	Leak	slow	hack	problem	rumor	crash	delay	dead

algorithms tend to prioritize specific content, thus potentially skewing sentiment analysis results, and interpretation of social media-based big data requires advanced tools for accurate interpretation (Beck et al., 2023; Brandes et al., 2022). Despite these challenges, social media offers a useful tool for analyzing customers' brand-related emotions and sentiments (Alantari et al., 2022).

Nevertheless, exclusive reliance on sentiment analytical CI presents key challenges. While providing firms with valuable strategic insight, it may limit the understanding of the underlying root causes of those customer emotions. For negative customer emotions, understanding these causes is critical to mitigating or eliminating such negative customer sentiment. These challenges are further compounded by technical algorithm intricacies, particularly the dictionaries used to discern emotions. Algorithm-based dictionaries often lack a comprehensive listing of affective subtypes. Moreover, despite recent technological advancements, interpreting human emotions in textual form remains challenging (see Table 7).

The listed statements illustrate key limitations in lexicon-based sentiment analysis models to capture specific customer emotions (e.g., sarcasm) accurately. To overcome these limitations, we employed topic modeling as a complementary approach to generate a more nuanced understanding of customer sentiment (Bastani et al., 2019; Salminen et al., 2022b; Vayansky and Kumar, 2020). Furthermore, sentiment analysis and topic modeling are synergistic approaches that can collectively be used to better understand customer sentiment.

Table 7
Sample challenging statements in the performance of sentiment analysis.

Customer's statement	Sentiment-based challenge for machine-learning applications
I do not dislike horror movies that much	Phrase with negation
Hating horror movies is not uncommon	Negation, inverted word order
Sometimes, I really hate this show	Adverbial modifies the sentiment
Oh! How much I love having to wait two months for the next series to come out!	Sarcasm
The final episode was surprising with a horrible twist at the end	Negative term used in a positive way
The film was nice to pass some time, but I would not recommend it to my friends	Difficult to categorize
I LOL'd at the end of the romantic scene	Typically challenging to understand new or slang terms

Source: Sentiment Analysis: A Definitive Guide (2022).

4.2. Generating customer insight through topic modeling: the case of FedEx

We employed NLP-based topic modeling to attain deeper insight into CI at the firm level, specifically focusing on FedEx. Prior topic modeling applications have demonstrated their effectiveness across industries, including fraud detection (finance) and analysis of patient feedback (healthcare), among others. In this study, ML algorithms were designed to delineate five predominant topics from the FedEx dataset, encompassing more than 200,000 posts (tweets). The topics shown in Table 8 highlight the key terms and their frequency in each topic. Following the table are more detailed discussions of each topic.

Topic 1 – Parcel Tracking: Our ML and NLP analyses reveal that customers' predominant concern centers on "parcel tracking," which involves tracing a parcel's location through its journey and updating the customer about its status and delivery date. The analysis identified challenges customers face with online tracking (e.g., website issues or difficulty finding relevant information), highlighting an operational gap that requires improvement. Examples of customer concerns voiced on X illustrate this point:

> @FedEx @FedExHelp so tracking for my new rugs says estimated delivery by end of day today (which isn't happening obviously because it's 8 PM), but there are no updates at all on where the package actually is. It just says the label was created.

> @FedEx hello, pls this is about 5 days now I sent a parcel down to China from Lagos, Nigeria. I have tracked the parcel, but no sign of movement on the tracking ID, pls can I get more clarification on this?

Table 8
Key tweet-based topics revealing customers' emotional expressions.

Topic Number	Dominant Words that Form the Topic (With Frequency)	Topic Label	Further Interpretation
1	0.021*"package" + 0.017*"delivery" + 0.015*"tracking" + 0.014*"find" + 0.013*"online" + 0.012*"shipping" + 0.012*"need" + 0.012*"can't" + 0.011*"not_working" + 0.010*"website"	Parcel Tracking	Online tracking of parcel/package delivery
2	0.080*"help" + 0.038*"support" + 0.034*"profit" + 0.028*"delivery" + 0.024*"send" + 0.024*"on-time" + 0.018*"told" + 0.017*"small_business" + 0.014*"sales" + 0.014*"win"	Small Businesses Services	How small businesses can use FedEx to deliver their products to end customers
3	0.159*"Better" + 0.138*"worse" + 0.026*"field" + 0.021*"dhl" + 0.015*"delivery" + 0.013*"slower" + 0.011*"usps" + 0.011*"ups"+ 0.011*"dhl" + 0.011*"time"	Performance Comparison	FedEx's Performance in Comparison to other service providers (e.g., DHL or UPS)
4	0.057*"package" + 0.036*"slow" + 0.028*"delivery" + 0.017*"driver" + 0.017*"late" + 0.016*"broken" + 0.016*"not_reliable" + 0.015*"delivered" + 0.013*"miss" + 0.012*"time"	Package Delivery	Timely delivery of packages by FedEx drivers
5	0.027*"job" + 0.021*"office" + 0.020*"customer_service" + 0.020*"express" + 0.019*"bad" + 0.019*"help" + 0.018*"problem" + 0.018*"worst" + 0.016*"ask" + 0.016*"status"	Customer Service	Customer expressing his/her satisfaction with FedEx customer service

Addressing these tracking challenges is critical to improving customer trust and satisfaction. Practical solutions include redesigning or upgrading online tracking system functionality and the user experience, implementing more reliable real-time tracking features and training customer service representatives to effectively handle tracking queries. These improvements can reduce complaints, strengthen customer loyalty, and create or boost the firm's competitive advantage. For example, customers' seamless, reliable tracking experiences can become a key selling point, attracting new customers. This would mitigate negative customer sentiment and advance positive brand engagement.

Topic 2 – Small Business Services: The second theme centers on utilizing small business services, supported by the company's "Small Business Hub," which offers guidance on cross-border shipping and market trends. This hub is a critical resource for small businesses, providing essential tools and information to navigate complex international markets. By leveraging these services, small businesses can enhance their operational efficiency and competitiveness. The topic exhibits a positive overall valence and suggests that small businesses using these services tend to experience positive outcomes, such as sales growth and new customer acquisition. As a result, both the small businesses and the firm benefit from improved customer satisfaction and enhanced firm performance.

These positive insights can be leveraged to strengthen relationships with small business customers. By expanding and promoting the "Small Business Hub," the firm can reach a broader audience and provide more comprehensive support to its clients. Showcasing success stories and offering tailored resources can significantly bolster the brand's reputation and attract new clients. This proactive approach enhances the perceived value of the firm's services and solidifies its position as a trusted partner for small businesses. Consequently, both the firm and its small business clients experience mutual growth and success.

By focusing on the specific needs of small business customers, the firm can identify areas for service innovation and improvement (Hollebeek, 2019). Addressing this customer segment's unique challenges and requirements is essential for building long-term trust and loyalty. Through continuous engagement and support, the firm can nurture stronger relationships with its small business clients, driving sustainable growth. Moreover, these efforts contribute to a deeper understanding of market dynamics and customer preferences, enabling the firm to adapt and evolve its services effectively. Ultimately, this customer-centric approach drives firm growth and ensures long-term success and competitive advantage in the market.

Topic 3 – Performance Comparison: The third theme focuses on customer evaluations of the firm's performance (vs. similar service providers like UPS, DHL, and UPS). In this sector, customers value providers that provide transparency (e.g., parcel tracking) and deliver promptly. This topic highlights the need for the firm to meet or exceed its rivals' performance to maintain or raise customer satisfaction and competitive positioning, as the following data points illustrate:

> @USPSHelp when did the USPS become just as bad at doing their job as FedEx and UPS? Absolutely terrible. I paid extra to have my package here last week, and now you're holding it because your driver is an idiot. You owe me for the shipping cost now.

> Thank God for @UPS! They know where their packages are and when they'll deliver them! @FedEx is terrible! Out for delivery four days in a row and still haven't received my packages. @FedEx can't/won't tell me anything.

This feedback suggests that the firm should benchmark its services against competitors to identify areas for improvement (e.g., by enhancing the delivery speed and reliability, developing marketing campaigns that emphasize the company's strengths, and showcasing improvements), meeting or exceeding customer expectations. Moreover, understanding the specific areas in which competitors excel can provide valuable strategic planning insights. By adopting best service practices, the firm can ensure that it remains competitive and responsive to customer needs. Such a continuous improvement approach is essential to sustaining long-term success in highly competitive markets.

Topic 4 – Parcel Delivery: The fourth theme centers on parcel delivery, representing a key source of customer dissatisfaction, particularly regarding delivery timing and service. Customers frequently express concerns about slow parcel delivery, delayed arrival, damaged goods, or unreliable service. This insight underscores the need for the firm to address the temporal and quality aspects of its delivery processes.

For example, one customer tweeted, "Idk who's working at FedEx but my package that's supposed to arrive today is going further away from me." Another noted, "FedEx said my friend's package was out for delivery yesterday. Never showed up last night or today, and it's now 8 p.m. FedEx, why?" A further example includes, "@lululemon placed an order, and it says my order was delivered via FedEx, but my package is missing. Who do I contact? I cannot get a hold of you via phone, and there's no listed email. Please help!"

Based on these findings, the firm is advised to optimize its processes for timely, reliable parcel delivery. Potential avenues for improvement include implementing advanced tracking systems, providing real-time updates, and training delivery personnel to handle parcels with care. These improvements should raise customer satisfaction and trust while boosting brand reliability and loyalty.

Topic 5 – Customer Service: The final theme centers on customer dissatisfaction with the level and quality of customer service (e.g., through unhelpful representatives, delayed responses, and unresolved queries). High-quality customer service is crucial in the transportation subsector, raising service quality through more timely deliveries and enhanced customer satisfaction. For example, one customer tweeted:

> @FedEx @FedExHelp HEY! Why is it so hard to contact someone from FedEx to help? Customer service has been no help at all. I shipped 215 orders of face masks out on Friday. Today, I find out that most of them were delivered to Memphis, and someone named M. P.

> @FedEx Hey FedEx - You delivered a big box to me, and it is NOT mine …. Waited on hold for over an hour to report and could not get through. Can you connect me with someone so I can let you know? Online help doesn't help either.

The firm can proactively address these issues by implementing advanced training programs, using value-laden customer relationship management (CRM) systems, and establishing comprehensive feedback mechanisms. Addressing negative delivery experiences promptly and effectively is crucial, as unresolved issues can significantly impact a company's reputation and customer retention. By prioritizing customer service improvements and ensuring the timely resolution of issues, FedEx can mitigate these risks and develop stronger customer relationships.

Addressing these concerns can also raise firm performance. Effective customer service is a key differentiator in competitive markets that can drive customer acquisition and retention. By prioritizing improvements in this area, the firm is expected to cultivate stronger client relationships and reduce churn. Continuous improvement and responsiveness to customer feedback are essential to increase customer satisfaction. By implementing the attained topic modeling insights, the firm can strategically address issues of concern and enhance service quality. Such a proactive approach is key to improving customer satisfaction, fostering loyalty, and maintaining an industry competitive edge. Through continuous monitoring and flexible adaptation, the firm can meet evolving customer expectations and remain a trusted service provider.

4.3. Exploring topic relationships

To enhance the interpretability of CI derived from topic modeling, we employed pyLDAvis to construct intertopic distance maps (see Fig. 8). These visualizations represent topics as points in a two-dimensional space, with proximity indicating thematic similarity (Mustak et al., 2021). Circle size corresponds to topic prominence in the dataset. Given the challenges of manually analyzing large datasets (Chintagunta et al., 2016; Nilashi et al., 2021; Sydney, 2020), these maps facilitate in-depth analysis. Multidimensional scaling reduces the dimensionality of word associations, allowing related topics to cluster visually (Mustak et al., 2021).

Intertopic distance maps have been deployed in a range of sectors. In healthcare, they have been used to identify prevalent patient concerns, enabling targeted service improvements. Similarly, these maps are used in finance to understand customer sentiment and boost service offerings. However, challenges relating to their implementation exist. The reduction of multidimensional data in two-dimensional space not only runs the risk of oversimplifying complex relationships, but map effectiveness is also contingent on data quality and algorithm parameters. A comprehensive understanding of these factors is critical to attaining accurate, actionable insight that drives strategic improvements and enhances the customer experience.

Through their close proximity, the intertopic distance map shows a rather strong correlation between "Parcel Tracking" (Topic 1) and "Services for Small Businesses" (Topic 2) for FedEx. This suggests that timely and accurate delivery updates are crucial for small businesses, impacting customer satisfaction and business continuity. This visual representation highlights the importance of reliable parcel tracking for small business clients, potentially driving loyalty and satisfaction through tracking improvements. Furthermore, the prominence of online parcel tracking as a primary customer concern aligns with its significant role in shaping customer perceptions.

The intertopic map also indicates that while "Performance Comparison" (Topic 3) and "Package Delivery" (Topic 4) receive similar attention levels from the firm's customers, "Customer Service" (Topic 5) received slightly less attention. Moreover, the separation between these topics in the intertopic map suggests a relatively low level of interconnectedness between them, highlighting the unique, specific nature of customer concerns in each area. For example, while performance comparisons focus on benchmarking FedEx against competitors, parcel delivery concerns center on service timeliness and reliability. While slightly less prominent, customer service issues still play a critical role in overall customer satisfaction and loyalty.

Based on this insight, FedEx can strategically prioritize its operations. The findings suggest that improving parcel tracking, in particular, is expected to bolster customer trust, perceived service reliability, and retention. Targeted communication strategies can also be developed to communicate tracking improvements to customers.

4.4. Validation of the findings

Natural language, characterized by its extensive dimensionality, poses challenges in achieving objective interpretation of data, especially with large datasets (Chen et al., 2019; Mustak et al., 2021; Schubert et al., 2017). This study demonstrates this complexity by applying sentiment analysis to 4 million tweets and subsequent topic modeling on a subset of 200,000 tweets related to FedEx. The multidimensionality of our analyses necessitates robust validation techniques. We employed t-distributed stochastic neighbor embedding (t-SNE), an ML method used to visualize multidimensional results (Schubert et al., 2017). Using eigenvectors from the covariance matrix, t-SNE reduces data to a lower-dimensional space while preserving maximum variance. This approach aids in understanding and validating complex relationships in the modeled topics.

While t-SNE is a powerful visualization tool, it has limitations. It can be computationally intensive and slow with large datasets. The results are sensitive to parameters such as perplexity and learning rate, requiring careful tuning. Moreover, the axes in the reduced-dimensional space may lack interpretability, as their focus is on preserving local

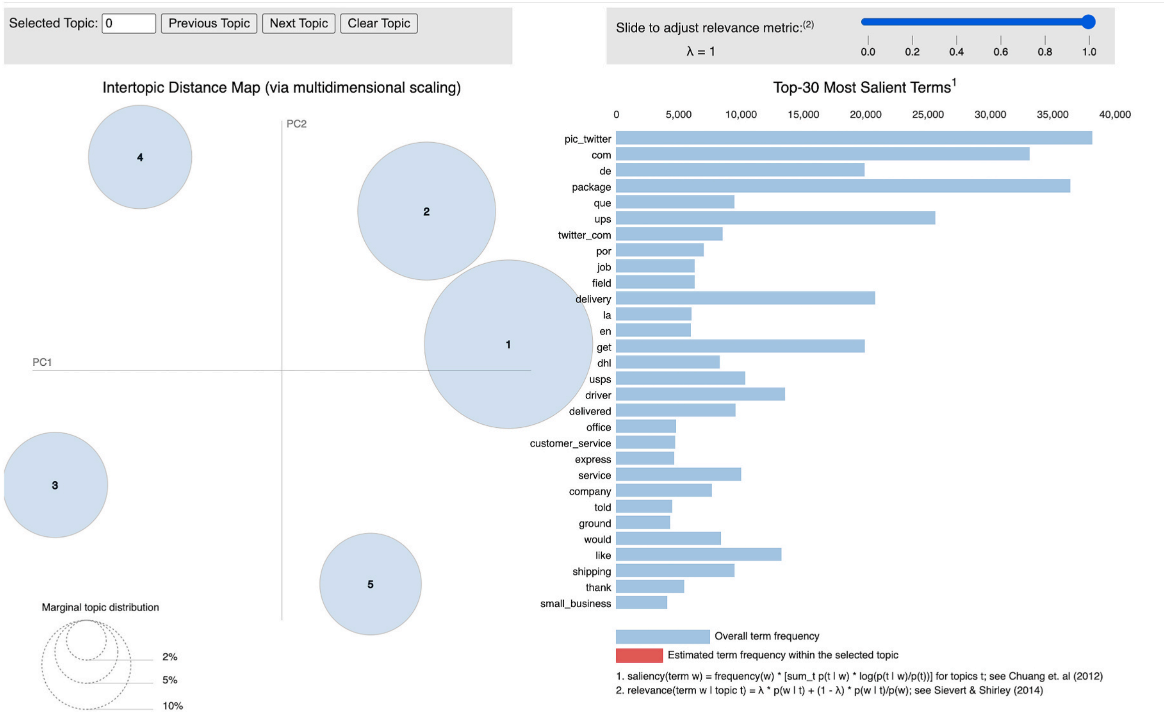

Fig. 8. Intertopic distance map for FedEx.

structures (vs. global relationships). Despite these challenges, t-SNE can reveal patterns and clusters that might be obscured when using higher dimensions. In this study, we apply this approach to validate our findings, thus demonstrating the value of advanced visualization techniques for understanding complex data relationships.

The findings reveal that t-SNE suitably represents numerous high-dimensional points in a 2D plane, preserving proximity among data points (Chen et al., 2019; Schubert et al., 2017). Fig. 9 demonstrates the consistency of the multidimensional data points with five identified topics, confirming the validity of our models. This visualization underscores the robustness of combining sentiment analysis with topic modeling as it accurately captures the underlying themes in the customer discourse for FedEx (Chen et al., 2019; Mustak et al., 2021).

5. Conclusion

5.1. General discussion

The generation of CI poses considerable challenges for firms across sectors and markets (Price and Wrigley, 2016). Overcoming obstacles related to data access, lacking availability of analytical tools, and the development of effective approaches to generate CI, is crucial (Berger et al., 2020; Salminen et al., 2022b). ML offers a powerful solution by facilitating the collection and analysis of publicly available UGC (Berger et al., 2020), thus empowering firms to generate valuable CI cost-effectively, ultimately enhancing their market intelligence (Bailey et al., 2009; Berger et al., 2020; Price and Wrigley, 2016; Said et al., 2015).

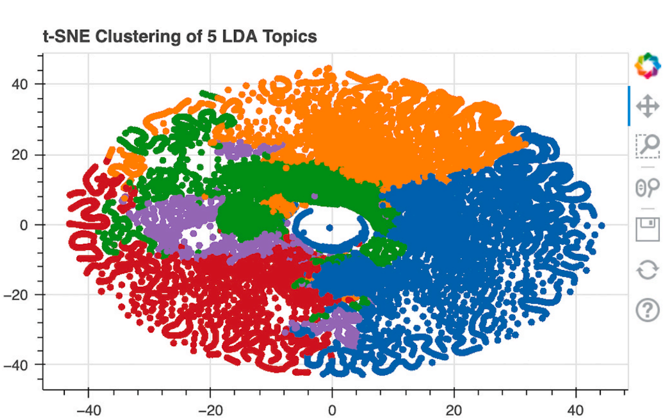

Fig. 9. t-SNE clustering of LDA topics for FedEx.

While ML offers significant benefits for the extraction of CI (Choudhary and Arora, 2024; Zaghloul et al., 2024), challenges remain. The complex nature of emotions in UGC, coupled with its vast amount of unstructured data, necessitates sophisticated analysis (Abu-Salih et al., 2018; Salminen et al., 2022a). This study addressed these challenges by demonstrating how NLP/ML can be combined to generate comprehensive CI. Specifically, our approach focuses on understanding customers' brand-related emotions and uncovering their underlying motivations. Thus, the proposed integrated NLP-ML approach provides a robust framework for firms to navigate the nuances of customer sentiment to distill actionable insight.

The increasing availability, sophistication, and relevance of data have transformed marketing research methods (Nilashi et al., 2021; Schaeffer and Rodriguez Sanchez, 2020). Traditional content analysis is increasingly being replaced with advanced computational approaches (Balducci and Marinova, 2018; Carlson et al., 2023; Liu et al., 2017), highlighting the need for accompanying methodological advancements (Alantari et al., 2022; Carlson et al., 2023). New approaches are critical to advancing the field, particularly by extracting deep insights from unstructured, multifaceted, or non-linear data (Balducci and Marinova, 2018; Berger et al., 2020; Choudhary and Arora, 2024). Our research contributes to this objective by presenting a method that involves extracting, cleaning, and structuring unstructured online content, which is then analyzed using modern robust ML algorithms to generate CI.

UGC on social media is a rich data source that unveils the multifaceted nature of customers' brand evaluations (Zhang et al., 2021). Therefore, developing an understanding of customer emotions holds significant value for firms. By delving into the underlying reasons for customers' specific brand-related emotions, firms can finetune their understanding of those actions that customers value and identify areas of strength and potential improvement. The proposed NLP/ML method leverages these technologies to generate CI, yielding cost savings for firms (Salminen et al., 2022b).

This study extends beyond the traditional applications of ML-based NLP and topic modeling (e.g., for branding/promotion). It demonstrates the versatility of this integrative method through its application to market research. Likewise, this approach may hold value in contexts including new product development, design, and engineering, thus broadening the strategic value of ML-based techniques and highlighting their ability to drive insight across business functions.

5.2. Theoretical implications

This study has important implications for further theory development in a big data era (Chen et al., 2019; Erevelles et al., 2016; Nilashi et al., 2021). Specifically, it underscores the potential of combining NLP/ML techniques to extract valuable consumer insights from vast, unstructured data (e.g., UGC). As such, this study aligns with a growing corpus of research that views AI and ML-powered methods (e.g., sentiment analysis and topic modeling) as the next frontier to understand consumers' brand engagement and perceptions (Culotta and Cutler, 2016; Praveen et al., 2024). By outlining and illustrating the proposed approach, the proposed method is expected to encourage researchers to re-evaluate the transformation of textual data into actionable CI through automated UGC analysis. Future scholars may wish to adopt or refine the proposed method, allowing them to transition from traditional (e.g., content) analysis to more advanced computational forms (Choudhary and Arora, 2024; Roelen-Blasberg et al., 2023).

Second, building on the proposed theoretical framework, which identifies three CI dimensions (i.e., instrumental, conceptual, and symbolic) (Said et al., 2015), our integrative adoption of sentiment analysis and topic modeling aligns with instrumental and conceptual CI. Instrumental insights focused on the application of knowledge to solve business problems resonate with the strategic applications of ML, as showcased in this research. For the conceptual dimension, we emphasize the need to understand the intricacies of consumer choice and behavior (Said et al., 2015).

This study also resonates with symbolic CI, which explores the psychological and symbolic aspects of consumer behavior (Macdonald et al., 2012). By leveraging customer information to justify or explain past actions and future decisions, symbolic insights help firms uncover the symbolic meaning associated with customers' behavior, encouraging a deeper exploration of stakeholder dynamics in the context of brand evaluation (Bharadwaj et al., 2013; Hollebeek et al., 2022; Kühl et al., 2020). Looking ahead, CI will see the likely integration of sophisticated (e.g., deep or reinforcement learning) AI models (Zaghloul et al., 2024), which can handle more intricate data structures, thus providing deeper insight. Moreover, multimodal data analysis, which combines text, images, and videos, is gaining traction (Mohri et al., 2018). This approach offers a more holistic understanding of customer sentiment and behavior. As technology advances, the fusion of advanced analytical techniques with traditional marketing research methods is expected to unlock new CI dimensions, giving businesses a competitive edge.

However, despite the potential of ML applications in marketing research, they also incur challenges (Choudhary and Arora, 2024; Mustak et al., 2021), including the need for large, high-quality datasets to train ML models (Erevelles et al., 2016; Hollebeek et al., 2024; Nilashi et al., 2021), which are costly to acquire and manage. Moreover, while the complexity of ML algorithms requires technical and marketing expertise (Berger et al., 2020; Mustak et al., 2021), algorithmic bias may also occur, requiring careful monitoring and verification to maintain accuracy and fairness. Nevertheless, ML applications in marketing research present exciting methodological advancements in the field. By investing in high-quality data, promoting interdisciplinary collaboration, and continuously improving algorithms, researchers will be able to fully leverage the transformative power of ML technologies (Balducci and Marinova, 2018; Berger et al., 2020; Mustak et al., 2021).

5.3. Practical implications

This study highlights the cost-effectiveness of using ML to analyze UGC compared to traditional methods, making it suitable for firms of all sizes. Beyond the cost benefits, this methodological approach is versatile and can be applied to various areas, including market research, product development, design, and engineering, allowing for its widespread implementation across the firm. The key practical implications derived from our analyses are as follows:

- *Invest in sentiment analytics tools:* Firms are advised to prioritize the acquisition or development of tools to assess customer feedback (e.g., on social media).
- *Train customer service representatives:* It is recommended to train customer service representatives to identify and address key emotional cues in customer interactions, enabling them to respond more empathetically and enhance perceived value.
- *Develop targeted marketing campaigns:* Firms should leverage insights from sentiment analysis to create targeted marketing campaigns that address specific customer needs and preferences.
- *Monitor brand sentiment:* Regularly monitoring brand sentiment across sectors is advised to identify positive sentiment benchmarks and track brand perception.
- *Prioritize responding to negative sentiment:* Firms should develop a clear strategy to respond to negative customer sentiment on social media, such as addressing concerns directly, offering apologies, or outlining solutions.
- *Identify emotional brand loyalty drivers:* Sentiment analysis should be used to understand the emotional drivers behind customer brand loyalty compared to competitive brands.
- *Conduct regular social listening audits:* Firms are advised to conduct regular social listening audits to identify emerging trends and potential areas of concern regarding customer sentiment.

These implications provide actionable insights for leveraging ML in analyzing UGC to enhance various aspects of business operations and customer engagement. However, despite its benefits, using social media data to generate CI also incurs challenges. Social media algorithms may amplify specific sentiments or trends, potentially skewing brand engagement or perceptions. Moreover, analyzing large datasets requires robust tools and methodologies to ensure the development of accurate, representative insights. By addressing these challenges, firms are expected to develop a more comprehensive understanding of their customers.

5.4. Limitations and further research

Despite its contribution, this study also has limitations. First, the findings are primarily constrained by the data source X (Tweeter), which limits tweets to 280 characters, restricting consumers' articulation of their brand-related emotions. Moreover, Twitter's demographics may not represent the population, introducing potential bias. To overcome these issues, we recommend that scholars replicate or extend our analyses using other UGC sources (e.g., Facebook, review sites like TripAdvisor, online customer forums like Apple communities, or e-tailers like Alibaba).

Second, this study relied solely on textual data to generate CI. However, customers often post different content (e.g., images on Instagram vs. videos on YouTube or TikTok). Therefore, extending our findings to image-or video-based data sources represents an interesting avenue for further research (Mustak et al., 2021). Our topic modeling results reveal operational issues related to the selected brand (FedEx), including parcel tracking and delivery, which may stem from the brand's utilitarian nature (Voss et al., 2003). Therefore, future researchers might apply the proposed method in other (e.g., more experiential or hedonic) contexts.

Third, our reliance on publicly available UGC may introduce bias (e.g., by potentially excluding specific target audience members). Therefore, we encourage future researchers to replicate our findings using representative samples (e.g., to validate or refine our results). Future research could also examine broader stakeholder insights, including those of suppliers and employees, thus further generating broader understanding (Hollebeek et al., 2022). However, our rule-based approach also has limitations, including its reliance on predefined lexicons that may fail to fully capture context-specific nuances or rapidly evolving social media slang (Alantari et al., 2022). Future research could thus integrate ML-based sentiment analysis to address these limitations. Combining VADER with supervised learning models trained on domain-specific data is expected to increase the accuracy and depth of CI-based sentiment analysis.

Fourth, exploring the ethical implications of using UGC for research purposes, which involves handling sensitive data that reflects personal opinions and experiences (Roma and Aloini, 2019), is critical. Researchers must safeguard respondents' data privacy and informed consent while maintaining data transparency. As technology advances, customer sentiment analysis will be steadily enhanced (e.g., by providing more accurate real-time insight). Advanced AI algorithms and improved data processing techniques can uncover deeper, more nuanced customer sentiments, which can be used to develop more effective, responsive business strategies.

In conclusion, this study demonstrates the power of combining NLP/ML techniques to glean valuable CI from UGC. Our analyses yielded a deeper understanding of customer sentiment, thus unveiling key future research opportunities. In the face of continued technological and methodological advances, the fusion of NLP/ML continues to hold promise in deciphering the complex tapestry of CI.

CRediT authorship contribution statement

Mekhail Mustak: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Heli Hallikainen:** Writing – original draft, Methodology, Conceptualization. **Tommi Laukkanen:** Writing – original draft, Methodology, Conceptualization. **Loïc Plé:** Writing – original draft, Conceptualization. **Linda D. Hollebeek:** Writing – original draft, Methodology, Investigation, Conceptualization. **Majid Aleem:** Writing – original draft, Visualization, Methodology, Formal analysis, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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