Mining Delivery Customer Claims in Social Media in Colombia, an Exploratory Analysis Applying Machine Learning Algorithms

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Abstract

The vast amount of available data, computational advances, and increasing social demands from customers present enormous challenges for delivery companies. Recognizing this need, we aim to investigate how such companies manage customer claims through X®. Our research, employing a sequential mixed-methods approach, began with a literature review through bibliometric analysis and subsequent interpretation via content analysis, concluding with the triangulation of theoretical findings with empirical evidence obtained from social media. For the final analysis phase, we collected and analyzed user mentions of delivery brands on X®, creating a data corpus—i.e., a sample collected through techniques—essential for our exploratory analysis. In this big data sample, we applied various natural language processing and machine learning algorithms, uncovering how users of these delivery companies tend to compare brands when making complaints. Furthermore, our research highlighted the psychological bias of users, who tend to polarize between love and hate for brands, respond to other user's posts, and engage in significant interactions with likes. Consequently, factors such as brand comparison, polarization between love and hate, and user interaction emerged as the main predictors of claims to these companies, underscoring the practical implications of our findings for the delivery industry.

Keywords: delivery customer claims, big data, social media, machine learning algorithms, polarization.

Introduction

Since the last decade, an enormous volume of digitally recorded opinion data has become available for humankind to analyze (Liu, 2012). This enormous volume of data receives the name of big data.

It is defined from the "Volume" -i.e., size of the data-, the "Velocity" -i.e., speed of increase of the data- and the "Variety" -i.e., type of data- (Balar et al., 2013).

The era of Big Data began over a decade ago, when computer scientists, physicists, economists, mathematicians, political scientists, bioinformaticians, sociologists and other scholars were devoted to analyzing it (Boyd & Crawford, 2012). Consequently, big Data has established itself as a technological, cultural and academic phenomenon based on the interaction of technology, analysis and the mythology it provokes (Boyd & Crawford, 2012).

Big Data as a technology can efficiently collect large sets of data (Chong et al., 2017) produced by and about people, things and their interactions (Boyd & Crawford, 2012). However, it not only includes collected data, but it also includes, among others, the rapid and combined analysis of large amounts of structured and unstructured data (Babu & Sastry, 2014) coming from various systems or sources of information (See-

To & Ngai, 2018). Therefore, big data and its analysis represent different stakeholders' opportunities in this context. Specifically for business, big data can improve business performance; first, however, it is necessary to change the decision-making culture (McAfee & Brynjolfsson, 2012).

Therefore, big data seems to be a good source for understanding organizational issues such as demand (See-To & Ngai, 2018) and even customer complaints (Basha & Rajput, 2019).

For these large data applications, unconventional tools are needed to manage and process the data (Balar et al., 2013), which also allows for comparing the accuracy of different algorithms - e.g., K-means and SVR - to select the best performing one (Lu & Chang, 2014). In addition, these applications often apply techniques of natural language interpretation, such as text mining, to identify, for example, word co-occurrence and predict sentiment polarity (Basha & Rajput, 2019).

Among the inputs they use is, for example, online word-of-mouth WOM, understood as a type of virtual currency that directly affects product sales, making them more or less attractive (Chern et al., 2015), among other inputs.

However, it is important to note how these applications are context-dependent since most words are ambiguous, and their meaning depends on the linguistic context in which they are used (Zhai, 1997).

Different authors raise the need to address big data in the business environment from different perspectives in the future.

Some do so from a strategic approach, suggesting future studies using Big Data to understand and predict the demand for products sold in online stores (Chong et al., 2017), support decision-making (Babu & Sastry, 2014), and even inspect quality at an aggregate level (Puts et al., 2015). Meanwhile, other researchers make recommendations from a tactical point of view. They suggest, for example, big data as a disciplinary field that requires social and behavioural scientists willing to collaborate with scholars from the natural sciences, engineering and computer science (Snijders et al., 2013). In other words, they posit the importance of collaborative and interdisciplinary studies to address big data applications (Pandey et al., 2017).

These tactical proposals require many things, for example,

(1) analytical infrastructure based on automated tools that facilitate big data analysis (Tan et al., 2015).

(2) The training of new talent in topics related to big data and its treatment (Waller & Fawcett, 2013).

(3) Incorporating additional variables -i.e., orthographic similarity, concreteness, bigrams or trigrams (Schuster et al., 2016)-.

Furthermore, (4) exploring different sources of information to improve the results (Justo et al., 2014).

After reviewing these proposals, we confirm the relevance of extensive data study from strategic and tactical perspectives such as those reviewed.

Thus, after understanding the current context, making some relevant definitions, and understanding the problems that arise, we identified the need to investigate how delivery customers claim on social media. With this purpose, we present below the theoretical framework where the theme is developed.

Then, we review the current literature on customer complaints to present the methodological protocol proposed to develop the fieldwork. In this fieldwork, we collected customer claims through the social media X® to two of the largest delivery companies in Colombia -Interrapidísimo and Servientrega-.

To finish discussing the results obtained and making some conclusions based on the research question

A theoretical framework for big data in organizational contexts

Managers and decision-makers view data as a driver of innovation and an essential source of value creation and competitive advantage (Tan et al., 2015). When these data are available in large quantities, they are referred to as big data and can be used in business environments for multiple purposes.

Among them are (1) to support supply chain operational decisions (See-To & Ngai, 2018), whether operational or front-line decisions (Babu & Sastry, 2014). (2) Understand demand structure (See-To & Ngai, 2018).

Moreover, (3) I want to know what others think more deeply than ever (Pang & Lee, 2008). Once the potential purposes of big data in the organizational context are recognized, it is necessary to detail its applicability.

Specifically, exploratory analyses are often applied when analyzing these enormous amounts of data (Schuster et al., 2016). This analysis tries to visualize and explore the data to discover hidden patterns and their relationships (Babu & Sastry, 2014), delivering tentative, inconclusive results (Alexopoulou et al., 2017). In the organizational environment, these exploratory analyses are not only applied to numerical indicators but also to text strings contained in opinions, feelings, evaluations, attitudes, and emotions typical of face-to-face spaces (Liu, 2012) and even in digital environments such as web forums, microblogging systems and social media (Saif et al., 2016). The most relevant technological advances for analyzing text strings are opinion mining and sentiment analysis (Pang & Lee, 2008), which apply natural language processing to perform content analysis (Pandey et al., 2017). This natural language processing can convert extensive, possibly unstructured text data into relevant data to solve a particular problem by interpreting patterns (Basha & Rajput, 2019). However, it is essential to caution that natural language interpretation is inherently context-dependent, i.e., most words are ambiguous, and their meaning depends on the linguistic context in which they are used (Zhai, 1997).

In other words, in this type of analysis, expressions that are not necessarily part of standard formal languages are reviewed, allowing the reflection of complex dynamics expressed by individuals and communities (Saif et al., 2016). This way, we understand exploratory analysis and natural language processing as fundamental tools for extensive data analysis, especially text strings.

Different authors recognize the relevance of big data in organizations as a driver of innovation, which can be applied through techniques such as exploratory analysis and natural language processing.

Among them, we find (1) some authors that conducted a content analysis by coding the critical incidents of a restaurant. Then, logistic regression algorithms identified how it is essential for customer satisfaction and how a specific solution to service problems relates to the consumer's desire to return to the restaurant (Susskind, 2005).

(2) Other authors propose personalized customer service, applying profiling and clustering techniques to recognize customer requests through free text (Smirnov et al., 2016).

(3) In the political environment, it is common to find large volumes of online data analyzed to monitor the position of voters, guide communication strategy, and prepare election campaigns. In this study, each word of an opinion (verbs, adjectives, nouns) is associated with a semantic marker related to polarity and intensity (Najar & Mesfar, 2017).

(4) Some authors consider customer satisfaction in e-commerce from their perception of the logistics service. In this process, they recognize the importance of logistics service dimensions such as availability, delivery

time, shipping costs, delivery reliability, product quality and condition, customer complaints and return policy, quality and perception of information, and e-customer satisfaction (Vasić et al., 2021).

(5) Others suggest that online companies pay attention to their customers' questions in the digital environment and display the answers online (Chong et al., 2017).

Finally, we find (6) others for whom online reviews of products and services with longer life cycles tend to generate few online discussions (Chern et al., 2015). These findings show the relevance of applying big data in organizational contexts, such as customer claims in delivery services, through exploratory analysis and natural language processing techniques.

Literature review about delivery customer claims

After introducing and presenting the research problem, we will conduct a literature review on customer complaints. To do so, we follow a sequential mixed approach (Mingers, 2001), starting with a bibliometric analysis and ending with a content analysis. Finally, in **Erro! A origem da referência não foi encontrada.**, we present the research protocol applied.

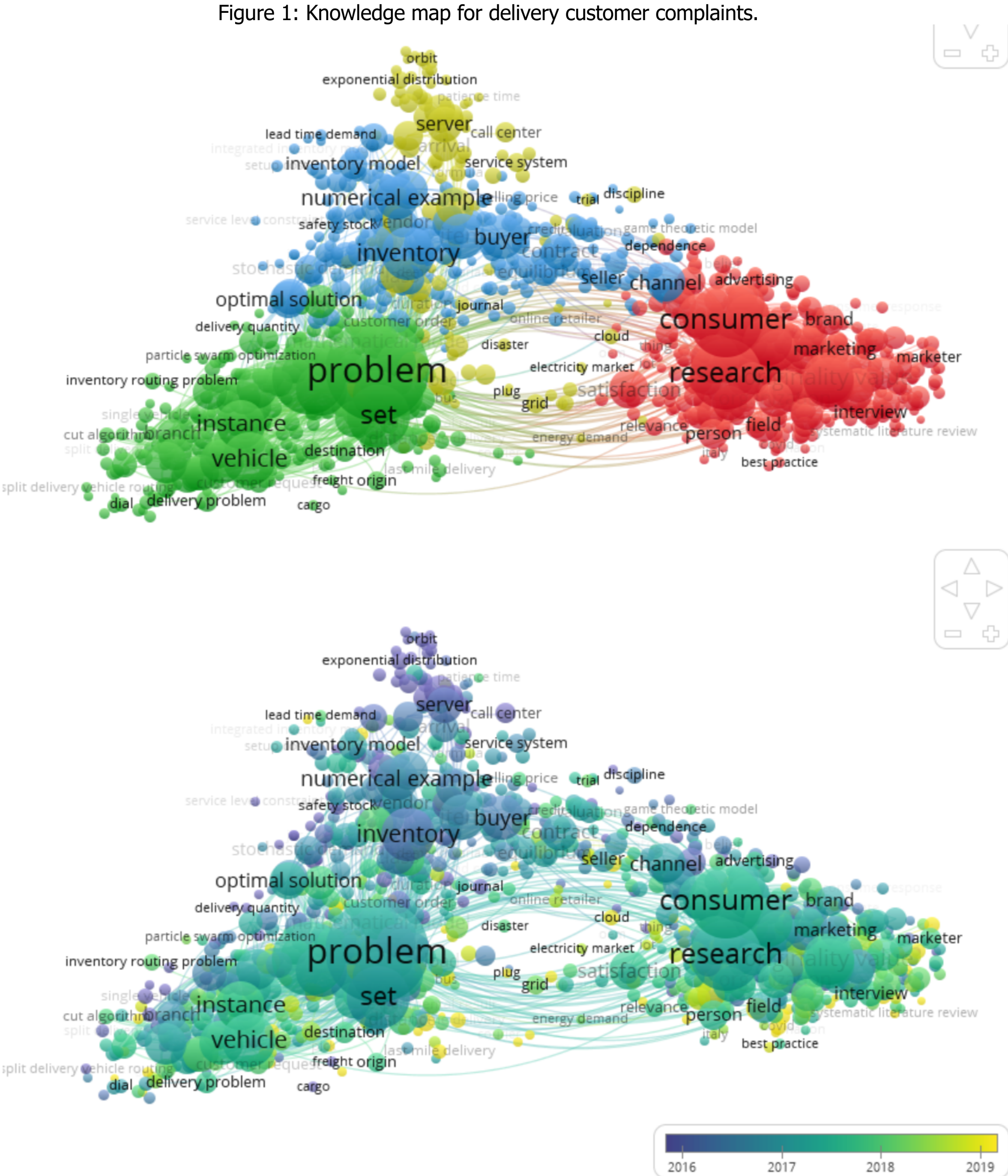
Table 1: Research protocol for literature review on delivery customer complaints.

Criteria	**Quantitative approach**	**Qualitative approach**
Role of the theory in research	Deductive	Inductive
Strategy of research	Simulation	Discourse analysis
Unit of Analysis	Word co-occurrence	Content of concepts
Sample	3.658 documents from the Web of Science. These documents result from the following search equation: (delivery or send* or dispatch or forward* or package or despatch or distribution) and (customer or consumer or shopper or user or buyer) and (claims or complaints or demands or calls or reclamations or requests or petitions or appeals or requisitions) (All fields). Filter for "Operations research management and science", "management", "engineering industrial", and "business."	Eighty-three documents from the Web of Science. These documents result from the following search equation: (delivery or send* or dispatch or forward* or package or despatch or distribution) and (customer or consumer or shopper or user or buyer) and (claims or complaints or demands or calls or reclamations or requests or petitions or appeals or requisitions) (All fields) (Title)
Variables	Dependent variable –e.g., the relationship between words- and independent variables –e.g., the occurrence of terms and concurrence between them,-.	Concepts and relations among them
Techniques for data analysis	Bibliometric analysis	Content analysis

Source: own construction.

Bibliometric analyses apply computational techniques that generate indices and indicators about scientific publications (Durieux & Gevenois, 2010), in this case, through the software VosViewer® 1.6.18 (van Eck & Waltman, 2007, 2010). This software processed the downloaded records using the search equation constructed following the citation pearl growing technique (Schlosser et al., 2006). Subsequently, the results obtained through this analysis were interpreted following a content analysis of the interpretative processes. After applying the PRISMA technique, this analysis considered the resulting publications (Moher et al., 2009). Figure 1 presents the knowledge map classified by year and cluster.

Figure 1: Knowledge map for delivery customer complaints.



Source: own construction.

The software groups the terms into four clusters. The first cluster stratifies consumer, role, implication, manager, satisfaction, organization, sector, purchase, and experience. The second cluster groups others like the problem, algorithm, set, vehicle, constraint, location, instance, route, vehicle routing problem, request, procedure, facility, and transportation. While in the third cluster, the algorithm relates terms such as inventory, buyer, channel, lead time, optimal solution, sensitivity analysis, total cost, contract, stock, and vendor. Finally, the fourth cluster contains terms like server, class, queue, scheduling, service time, probability distribution, numerical result, load, arrival, limit, station, and performance measure.

Cluster #1 – Stakeholders and Delivery Service

This first cluster groups different proposals for delivery service issues and their stakeholders, focusing mainly on customers. For example, after reviewing incidents, Susskind (2005) identified how correcting a service failure impacts customer satisfaction and re-purchase (Susskind, 2005). Likewise, Smirnov et al. (2016) propose personalized customer service or differentiated development models and strategies (Cho et al., 2021), in which they apply profiling and clustering techniques to predict consumer actions and interests by recognizing requests given in the form of free text (Smirnov et al., 2016). With this same focus on the customer, other proposals emerge that focus on the nature of the service-i.e., availability, delivery time, costs, reliability, quality, complaints, returns, information management, and satisfaction-and how this determines customer satisfaction (Vasić et al., 2021). These proposals review the role of customers during delivery services phases and their evaluation, but there are other points of view, which we will present below.

Alternatively, others continue focussing on consumers but in virtual environments, recognizing, for example, that the web contains information about what consumers search for, comment on, and buy in the real economy (Bughin, 2015). It means that the virtual environment represents a helpful input for organizational management (Pandey et al., 2017). It constitutes a corpus of data or big data that can support organizations' customer experience and value creation (Balar et al., 2013). In this virtual context, some review interactions on social media, while others analyze reviews. Among those that focus on interactions are some that are recognized as the most popular big data sources among companies: tweeting, videos, click streams and other unstructured sources (Tan et al., 2015). Researchers extract interaction indicators from these sources -i.e., tweeting, liking, commenting and rating- which provide information about the attention that a user or consumer pays to a particular object/product (Lassen et al., 2014). On the other hand, there are other authors for whom word-of-mouth is closely related to consumer behaviour (Chern et al., 2015). After reviewing online reviews, they discovered that the percentage of negative reviews has a more significant effect than positive ones, suggesting a negativity bias (Cui et al., 2012). Overall, we can recognize the virtual environment as a strategic field that must be considered while reviewing delivery customer claims; however, other stakeholders can still be included, as we will see below.

Finally, we found that few authors focus on reviewing the phenomenon from the perspective of the shareholders or owners of the brand. Some of them, for example, identified how customer reviews could characterize brand value, price and product type (See-To & Ngai, 2018). In this way, we complete the journey around delivery service review from the perspective of stakeholders, especially from the customer's perspective.

Cluster #2 –Transportation

Fast and cost-effective delivery of products is a complex optimization problem, where it is usually modelled with the minimum transportation cost and the penalty of timeliness and tardiness (Yang et al., 2020). This logistic problem has been addressed from different perspectives, some of them, for example, group customers according to their demand attributes rather than static geographic ownership (Hu & Sheu, 2003). Others model the service by considering demand, network topology, tariff class and quality of service, reaching an insightful analysis (Bilegan et al., 2022). At the same time, others propose a planning strategy for the coexistence of static and dynamic charging facilities for electric vehicles used in routing (Zhou et al., 2023). They even involve the public transport network to save energy in last-mile delivery with drones (Moadab et al., 2022), demonstrating how incorporating heterogeneous battery characteristics reduces the total cost by 36% compared to the baseline scenario (Sadhu et al., 2022). This shows the relevance of the logistics problem to be solved, the multiplicity of approaches and the usefulness of recent technological developments for modelling or representing logistics phenomena.

Cluster #3 – Stock

Big Data can be applied to organizational domains throughout the product lifecycle (Li et al., 2015). For example, with big data extracted from social media, predictive models can be created, insights about customers can be gained, and many other applications can be used (Lassen et al., 2014). Among the most popular applications is stock level control, where big data has been recognized as a valuable source of information for forecasting the level of sales and, consequently, for demand structuring (See-To & Ngai, 2018). They discover how large volumes of positive and negative online reviews, discounts, free delivery (Chong et al., 2017) and other web sources (Cui et al., 2012) posted by customers can be used to predict sales (Chern et al., 2015) and design e-marketing strategies (Cui et al., 2012). Under this premise, online word-of-mouth can be understood as a virtual currency directly affecting inventory levels and product sales, making them more or less attractive (Chern et al., 2015). In this way, by reviewing delivery customer claims, valuable insights can be obtained when managing stocks.

Cluster #4 – Scheduling

High competitiveness in industrial practice has encouraged companies to save costs in logistics activities whose percentage share in costs is high (Sydneyta & Komarudin, 2017). Tools such as vehicle route scheduling emerge to achieve such cost reductions, which seek to reduce delivery times, maximize profit and even lower labour costs. Among the authors who review time optimization are some who try to minimize transportation costs, achieve punctuality, reduce tardiness (Yang et al., 2020), decrease the total distance travelled, and maximize installed capacity (Sydneyta & Komarudin, 2017). From a dynamic approach, others propose constantly updating routes in real time for urgent deliveries (Zheng & Gu, 2018), seeking to satisfy customer requests at the given interval (Syahputra et al., 2018). Therefore, there are other authors who, for point industries where customer demand depends on the quoted delivery time, seek to maximize their profit by quoting different delivery times for all customer groups (Jin et al., 2013). Finally, we found other researchers who refer to the scheduling of logistics activities, comparing the pertinence of transaction quantity-based pricing policy to subscription or membership-based pricing policy (Chen et al., 2022). Thus, we complete our tour around proposals that review delivery customer claims by identifying service reviews from the perspective of stakeholders, primarily the customer, as the mainstream of the study, followed by other tactical decisions associated with transportation, inventory levels, and scheduling activities.

Research protocol for the exploratory analysis

After presenting the research problem and completing the literature review on delivery customer claims through bibliometric analysis and its subsequent interpretation in the content analysis, in Table 2, we present the research protocol. This protocol presents the research approach, the strategy to be implemented, the study sample, the variables involved, the data collection procedure and the data analysis techniques (Escobar-Sierra et al., 2021).

Table 2: Materials and methods to conduct exploratory analysis.

Decision	**Quantitative approach**
The role of the theory in the research	Deductive
Question of the research	We identified the need to investigate how delivery customers claim on social media.
Unit of Analysis	Structure of consumer claims in social media
Sample	We scraped X® comments from the official accounts of two of the largest delivery companies in Colombia (Servientrega® and Interrapidisimo®).
Variables	Text strings or words
Techniques for data collection	Social media comments in Spanish scraped from X® (Sullivan & Forrester, 2019).
Data analysis technique	To summarise data, find hidden relationships and make predictions, we use explanatory analysis (Myatt, 2007) using the Python programming language.

Source: own construction.

To analyze delivery customer claims through social media, we selected two Colombian companies (Servientrega® and Interrapidisimo®) dedicated to courier services. For these two companies, we identified social media users' mentions of the companies.

Results of the exploratory analysis

For this phase, we follow Myatt's (2007) proposal. When referring to the phases for developing exploratory analyses, he proposes four stages: during the first, he suggests defining the problem; in the second, preparing the data; in the third stage, implementing the analysis; and in the fourth, deploying results. Accordingly, we applied natural language processing (NLP) and its libraries in Python NTLK and scikit-learn (Kaye et al., 2017) after recognizing opinion mining and sentiment analysis as part of the most relevant technological advances for analyzing others' opinions (Pang & Lee, 2008).

Problem definition

Consequently, we asked ourselves how delivery customers complain on social media. To do so, we compiled the mentions that X® users make of two of the largest delivery companies in Colombia (Servientrega® and Interrapidisimo®).

Data Preparation

The data were extracted from X® using the Twint library of the Python programming language. Specifically, we extracted the mentions made by media users to the official accounts of each delivery brand with operations in Colombia – South America. The consolidated sample is presented below in Table 3.

Table 3: Number of posts and comments scraped from Rappi's® official accounts.

Delivery company	**Number of collected mentions**
Interrapisimo®	5.900
Servientrega®	5.646

Source: own construction.

To run the analyses, we used the Jupyter-notebook® web code editor as the interface to process the data. Both delivery brands generate a large volume of interactions and mentions on social media, so we collected an equivalent sample of about 6,000 mentions for each. After scraping the data, we conducted a preliminary review of its structure to determine the characteristics of quantity, frequency, length, entity and type of data. Once the corpus of text strings from the mentions described in Table 3 was consolidated, we cleaned the data. This means we standardize the strings, unifying upper and lower case, eliminating special characters, and even lemmatizing or eliminating inflectional endings to return each word to dictionary form. Once these phases are completed, we start with the analysis.

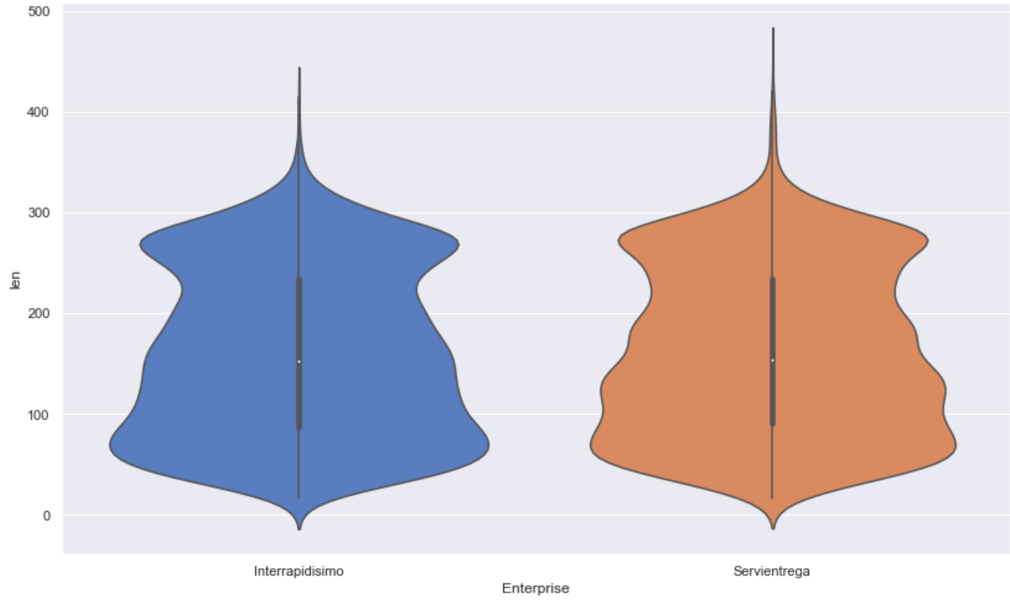
Implementation of the analysis

This phase is the most critical stage in the exploratory analysis. Here, patterns or differences are identified using graphs, tables, and statistics that can answer the research question formulated. Specifically, we identify particular behaviours in the data to infer general questions about them and their relationships (Downey, 2015), as developed below.

Length of each comment

The violin plot is similar to the box-and-whisker plot, but unlike the box-and-whisker plot, the components of the plot estimate the density of the data distribution rather than data points (Pancer et al., 2019). Next, in Figure 2, we present the violin plot with the average length of mentions made by users of both delivery companies. This type of analysis is valuable because, according to previous studies, the increased word length is related to increased activation in occipital areas related to visual analysis (Schuster et al., 2016).

Figure 2: Violin plot of the average length of comments mentioning Interrapidisimo and Servientrega.



Source: own construction.

The average length of the mentions made to the delivery companies' accounts is similar for both cases and close to 150 characters. However, Servientrega presents the highest number of extreme values for mentions, even though the distribution for the two companies is asymmetric, indicating the predominance of mentions between 150 and 300 characters.

Word cloud

Next, in Figure 3, we present the word cloud. It shows the words or unigrams with the highest number of occurrences in the data corpus, composed of the mentions made by the different users of the delivery companies. The analysis of this data type is relevant to verify the central themes on which the discussion about the services provided by the companies revolves.

Figure 3: Word cloud for the unigrams with the highest occurrence in the mentions of Interrapidisimo and Servientrega.

Source: own construction

When reviewing the most frequent unigrams in the Interrapidisimo and Servientrega data corpus, we identified some common elements and others particular to each brand. For example, for both brands, there are (1) negative descriptions of their delivery service, being more frequent for Interrapidisimo, (2) differentiation between business customers and natural persons when talking about customers and companies, (3) complaints to regulatory bodies, specifically to the superintendence which is who controls them in Colombia, (4) criticisms to the guides or labels where they relate the shipping data, and (5) allusions to be waiting for a response on the shipment of their packages. On the other hand, only in the mentions of Interrapidisimo does the name of the brand and its direct competitor appear, while for Servientrega, there are words of gratitude.

Bigrams and Trigrams

There are several methods to convert plain text documents into instances with relevant attributes for analysis (Bramer, 2007). For instance, we could count the number of occurrences of specific words—i.e., unigrams—or perhaps any combination of two or three consecutive words (bigrams and trigrams, respectively) (Bramer, 2007; Mu et al., 2012). The words with the highest occurrence in the collected sample are referenced in the previously presented word cloud. Therefore, we will now review the most frequent bigrams and trigrams.

- **Bigrams in the mentions of Interrapidisimo:** '@interrapidisimo @sicsuper', 'pésimo servicio', '@interrapidisimo @interrapidisimo', 'señores @interrapidisimo', '@interrapidisimo peor', '@sicsuper @interrapidisimo', 'servicio cliente', 'servicio @interrapidisimo', 'peor empresa', '@sicsuper @supertransporte', 'peor servicio', '@interrapidisimo servicio', '@interrapidisimo @iepaoficial', '@interrapidisimo pésimo', 'quedamos atentos', '15 días', 'atentos comentarios.', 'mal servicio', 'servicio tan', 'días esperando'.
- **Trigrams in the mentions of Interrapidisimo:** 'quedamos atentos comentarios', '@interrapidisimo peor empresa', 'pésimo servicio @interrapidisimo', '@interrapidisimo peor servicio', '@interrapidisimo @sicsuper @supertransporte', 'favor coméntanos dm', '@interrapidisimo pésimo servicio', 'colaborar quedamos atentos', '@interrapidisimo pésimo servicio,', 'peor servicio mensajería', 'atentos comentarios. @servientrega_ms', 'coméntanos dm novedad', 'cordial saludo, preocupa', 'comunícate vía dm', 'detalle novedad indícanos', 'novedad indícanos podemos', 'indícanos podemos colaborar.', 'podemos colaborar. quedamos', 'peor empresa mensajería', 'servicio tan malo'.
- **Bigrams in the mentions of Servientrega:** '@fcfseleccioncol @cervezaaguila', '@cervezaaguila @bancolombia', '@bancolombia @movistarco', '@servientrega_ms @sicsuper', '@servientrega_ms @servientrega_ms', '@sicsuper @servientrega_ms', '@movistarco @colombiana_ln', 'pésimo servicio', 'servicio @servientrega_ms', '@servientrega_ms peor', '@colombiana_ln @adidasco', 'señores @servientrega_ms', 'servicio cliente', '@servientrega_ms pésimo', '@adidasco @betplayco', '@servientrega_ms si', '@betplayco @servientrega_ms', 'peor servicio', 'mal servicio', '@servientrega_ms servicio'.
- **Trigrams in the mentions of Servientrega:** '@fcfseleccioncol @cervezaaguila @bancolombia', '@cervezaaguila @bancolombia @movistarco', '@bancolombia @movistarco @colombiana_ln', '@movistarco @colombiana_ln @adidasco', '@colombiana_ln @adidasco @betplayco', '@adidasco @betplayco @servientrega_ms', 'pésimo servicio @servientrega_ms', '@movistarco @colombiana_ln @betplayco', '@colombiana_ln @betplayco @adidasco', '@betplayco @adidasco @servientrega_ms', '@servientrega_ms pésimo servicio', '@servientrega_ms peor empresa', '@servientrega_ms peor

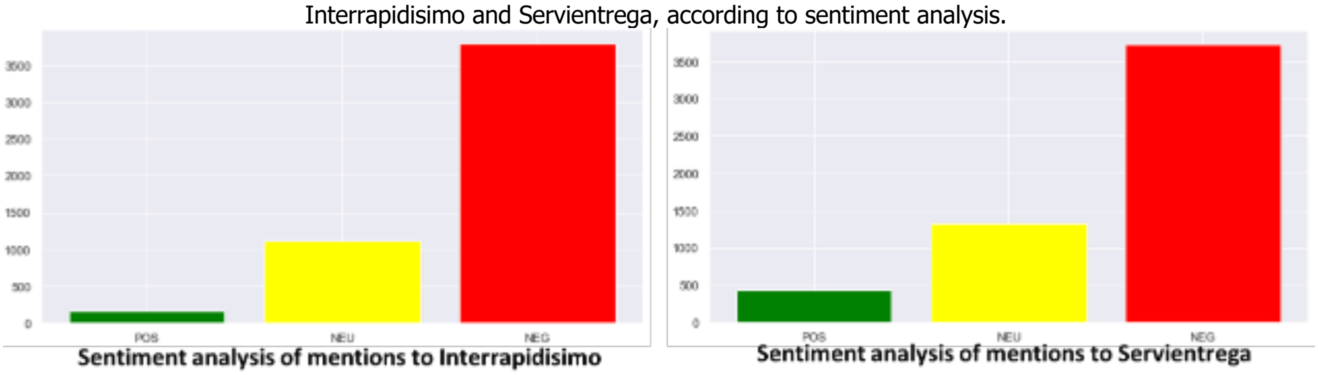
servicio','@servientrega_ms pésimo servicio,', 'femsa 📲 @telefonica_col', '@servientrega_ms mal servicio', 'cola femsa 📲', 'empleadores sector privado', 'organizaciones: 🥤 coca -', '📲 @telefonica_col 🔌 '

Among the most frequent bigrams or trigrams for both brands are (a) mentions of control agencies, the brand itself or other popular brands at the national level and (b) criticism of delivery companies and their delivery services. It is also important to highlight that in the case of Interrapidisimo, the company seems to respond to its users by inviting them to contact them through direct messages to manage their claims. Only in the case of Servientrega are emojis within the most frequent pairs or trios of words.

Sentiment analysis

Next, using natural language processing algorithms, we will classify each comment according to its sentiment—i.e., positive, negative, or neutral. This analysis is achieved by applying classification algorithms (Zulkifli & Lee, 2019) that categorize each text string that makes up the mentions made to both sharing brands according to their sentiment or polarity level.

Figure 4: Number of positive (green), neutral (yellow) and negative (red) mentions of Interrapidisimo and Servientrega, according to sentiment analysis.



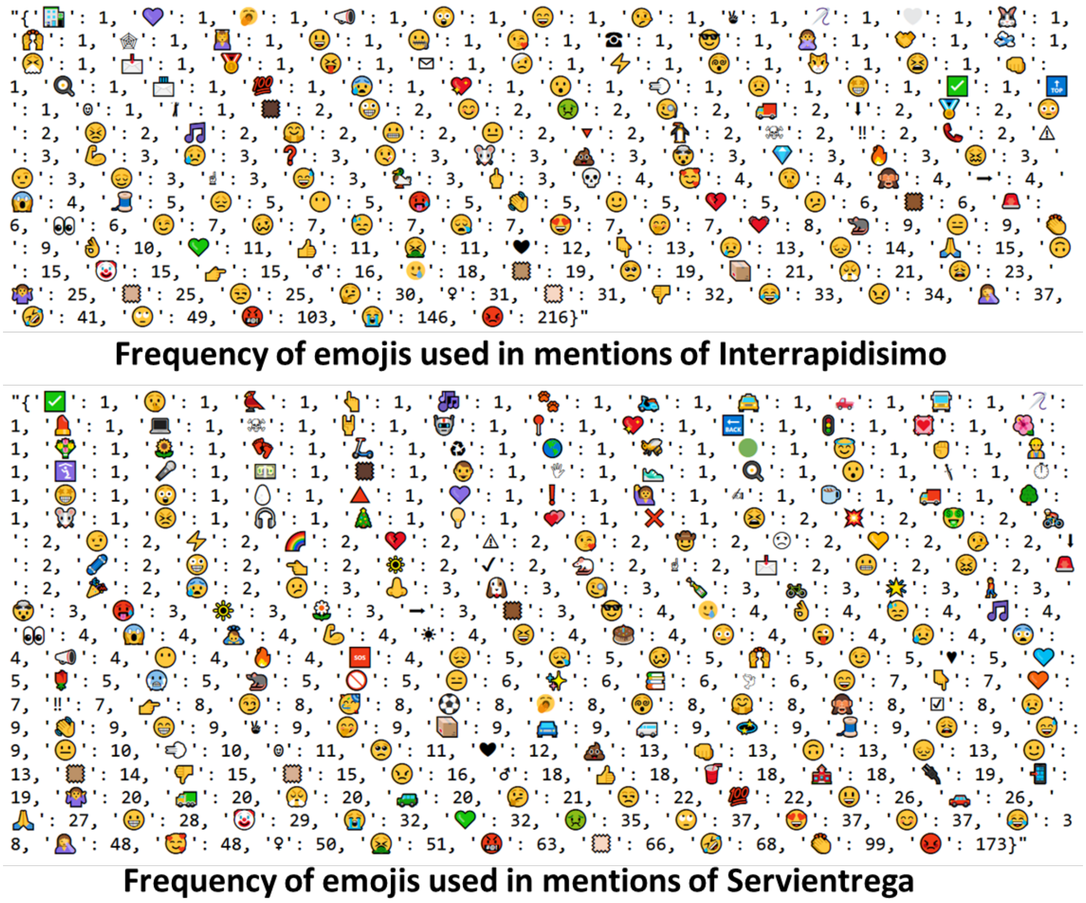
Source: own construction.

After classifying the sentiment of the mentions made to Interrapidisimo and Servientrega, we identified a negative bias for the former compared to the latter. We observed this because, having very close sample sizes, there is a more significant number of negative mentions in the case of Interrapidisimo. While Servientrega, despite having mostly negative mentions, has more positive mentions than Interrapidisimo.

Emojis

Emojis, nowadays, are more than simple images. Their popularity is growing thanks to social media, where they have positioned themselves as a way to express emotions and communicative intentions among human beings (Kaye et al., 2017). Recognizing their importance, we characterize their use in the mentions of both delivery companies below.

Figure 5: Frequency of emojis used in mentions of Interrapidisimo and Servientrega.



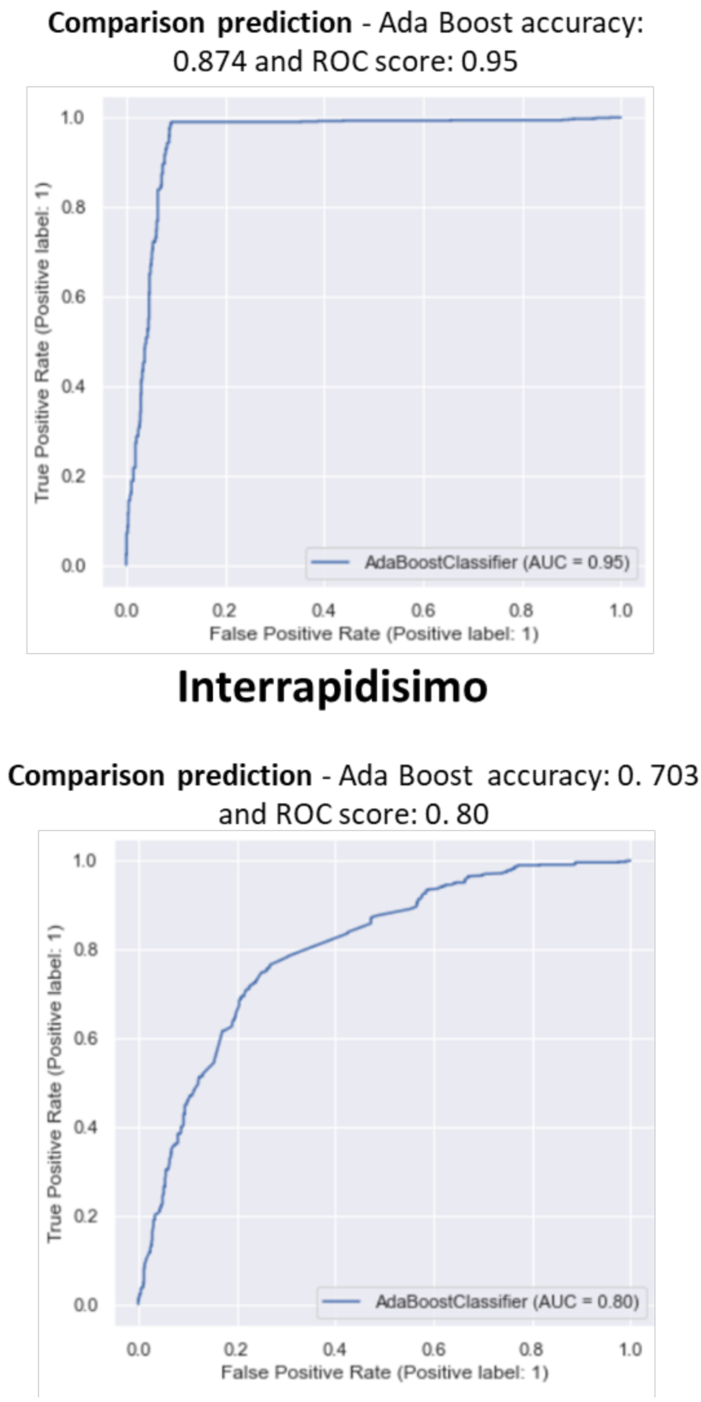
Source: own construction.

Several relevant aspects were identified upon checking the frequency of emojis in the mentions made to the official accounts of the two delivery companies. First, the red laughing face emoji is the most recurrent for both accounts, referenced in the abusive category by Purba et al. (2018). Likewise, we identified the yellow emoji crying from laughter as another of the most used in the mentions made to both brands; this emoji is categorized as happy (Purba et al., 2018). On the other hand, we noticed that the second emoji with the highest occurrence in the mentions of Servientrega is the applause categorized in the praising class (Purba et al., 2018), while the second most used emoji in the mentions of Interrapidisimo is the yellow face crying, categorized as sad (Purba et al., 2018). In this context, abusive emojis are recognized as the most popular category for both brands. However, we notice how the emojis Servientrega mentions have a favourable symbolic load compared to those of Interrapidisimo.

Prediction with m|achine learning algorithms

To complete the implementation phase of the ongoing analysis, we now configure a predictive analysis by applying machine learning algorithms to identify which independent variables—i.e., x—affect the selected dependent variable—i.e., y. In this case, we consider independent variables available in the collected database or created through feature engineering techniques such as the level of polarity (i.e., positive, negative, and neutral); the time of the post; the use of certain elements such as mentions, URLs, photos, videos, and hashtags; and audience reactions such as the number of replies, likes, and retweets. The dependent variable we aim to predict is the potential comparison with other brands. To configure the predictive models and train them with the mentioned independent and dependent variables, we compared the performance of five types of algorithms: Logistic Regression, Classification Tree, AdaBoost Classifier, Random Forest Classifier, and K-Nearest Neighbor (KNN) (Flach, 2012). For each brand considered, we selected the algorithms that achieved the highest predictive power, i.e., those with the highest accuracy, as evidenced in Figure 6, where a larger area under the curve indicates better predictive power.

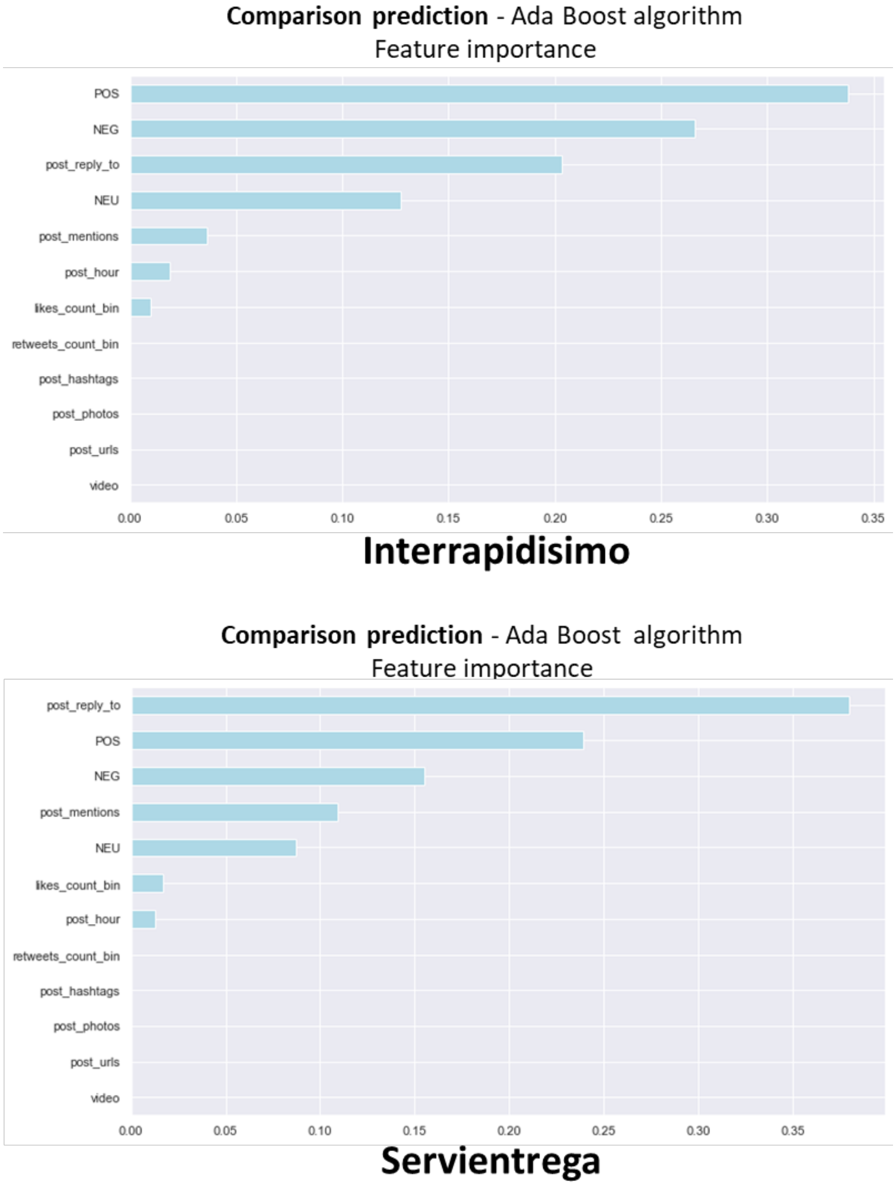
Figure 6: Area under the ROC curve for predicting claims comparing brands with competitors



Source: own construction.

AdaBoost's algorithm achieved the highest predictive power for both cases—i.e., Servientrega and Interrapidisimo. Subsequently, we verified the relative significance of each independent variable on the prediction of the selected dependent variable; this relative importance is graphically presented in Figure 7, where the independent variables with the highest predictive power on brand comparison (the dependent variable) are listed in order of importance.

Figure 7: Relative importance of predictors of claims comparing brands with competitors.



Source: own construction.

Thus, we can infer with a precision of 87% for Interrapidisimo and 70% for Servientrega that among the main predictor variables of the brand's comparison with its competitors is the polarity of the publication—i.e., its positive, negative, or neutral content—the response to other tweets, the likes, and the mentions it contains.

Deployment of results

This finding means that polarising message structures, which respond to other social media users with many likes and mentions, will likely compare the brand with one of its competitors. For Interrapidisimo, extreme polarity -i.e., very positive or negative content- the response to other messages and the high number of likes are the main predictors of claims comparing the brand with its competitors. For Servientrega, the results seem to indicate that the higher the response to other users, the more polarised the comment and the higher the number of likes, the greater the probability of containing comparisons in customer complaints. It would highlight the psychological bias of users of delivery companies, who are polarised between love and hate for brands and express their complaints on social media by responding to the publications of other users and achieving significant interactions with their likes.

Discussion of results

Our findings agree with some of the previous recommendations of other authors while differing from those of some others. Among the authors with whom our results agree are those who propose this type of study as collaborative and interdisciplinary (Pandey et al., 2017) because they involve, for example, engineers, computer experts, social and behavioural scientists (Snijders et al., 2013), among others; as it happened to us. Likewise, in our study, we use specialized analytical infrastructure (Tan et al., 2015) -Jupyter Notebook with Python- and also incorporate additional variables created through feature engineering (Schuster et al., 2016)-e.e., level of polarity and the presence of specific text strings-, as proposed by some authors.

In this way, we corroborate from a practical point of view the future recommendations of authors who had previously reviewed big data in research contexts such as ours.

On the other hand, among the authors with whom our findings differ are some that consider it from a strategic or tactical point of view. For example, from a strategic point of view are those who propose the use of Big Data to understand and predict the demand for products sold in online stores (Chong et al., 2017), support decision-making (Babu & Sastry, 2014), and even inspect quality at an aggregate level (Puts et al., 2015). From the tactical point of view, we found some recommendations, such as training talents (Puts et al., 2015) and exploring different sources of information (Justo et al., 2014), to which we also disagreed. Consequently, we complete the tour around the authors with whom we agree and differ and then go on to present the conclusions and future lines of our study.

Conclusions, limitations, and future research

Customers of the leading delivery companies in Colombia (Interrapidisimo and Servientrega) complain on social media, comparing the brands with their competitors. Specifically, by comparing them with their rivals, users seem to create polarising messages of love and hate that respond to other social media users and reach significant levels of interaction with likes. These findings highlight the psychological bias of delivery company users, who, polarised by love or hate for brands, express their grievances on social media by responding to other users' posts and reaching significant interactions with likes.

The proposed approach could be replicated in future studies that intersect topics related to logistics, marketing, and organizational management. Our findings, especially the proposed methodology, represent a novel approach to big data. Unlike previous studies, we utilized big data extracted from customer complaints on social media to predict sales levels or service quality. In this case, we applied it to understand how customers complain and the psychological predictors of these complaints, primarily based on brand comparisons with competitors.

Starting from a general research question like the one we formulated and implementing exploratory analysis techniques typical of data science allowed us to understand the big data available and refine the research question based on the results obtained. Initially, we tried to understand how customers complained on the social media of these Colombian delivery companies. However, once we understood the general features of this type of claim, we discovered, based on particular word frequency, that it was necessary to inquire about how users compare them with rival brands during a complaint. This way, we find the main predictors of complaints based on comparisons with rival brands made through social media X®.

Among the limitations of our study, we highlight the potential to include a comprehensive review of all Colombian delivery companies and a more substantial amount of data extracted from social media. We also identified that working with natural language processing (NLP) analysis of text strings written in Spanish could represent a disadvantage. This limitation arises from comparing the performance of analyses based on text strings written in English or other languages, which benefit from more collaborative development in Python programming.

Our findings are relevant to both the business sector and academia. For the business sector, it is essential to understand the relationship between brand building, logistics service, and marketing to determine, for example, which logistics management strategies can help generate loyalty among users. Meanwhile, for academics, integrating these topics, which have been studied separately, is significant.

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