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BANKS ON TWITTER: FROM SINGLE MESSAGE TO VISUAL ANALYTICS STRATEGIES

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Abstract

This paper aims to understand the structure and the dynamics of customer interactions with banks by social media. We use those interactions as a proxy to develop a social media strategy with visual analytics tools. Thus, this paper presents a visual analytics evaluation for some Colombian banks to identify the customer sensation about services and products through social media and their temporal interactions. Our approach detects those visual analytics allowed banks to understand the brand situation, products, services, and the implementation of social media strategies on a temporal small-scale. Findings provide advances in the real effects of Colombian banks' social media strategy and the low yields for investment in brand building strategy. We concluded that banks need to implement a social media strategy under the data-driven concept, where the added value will be customer acquisition and retention.

Keywords: Banking, Competitive intelligence, Data visualization, Social media, Visual analytics

1. Introduction

Banking services usually aim at a specific group of people, but technological and digital transformations achieved greater financial depth and new possibilities to access banking services. In this century, the customer relationship is not an exclusive affair of a physical branch as it had been for decades. Today, access to banking services is mostly directed towards a digital process that makes it easier for customers to interact with banks through technological platforms. Additionally, banks participate in social media interactions and enter a scheme where these networks are referents of banking services' characteristics, opinions, feelings, experiences, and perceptions. In other words, the customer relationship is different because it changed from physical branch to technological platforms and social media [1-3], i.e., the customer interacts with banks in real-time but on a smaller temporal scale.

Social media has been changing the interaction between firms and customers, and several scholars had proposed different frameworks to evaluate social media and customer dialogue. In this group, the social media had created a democratization of corporate communication [4], new firm-customer interactions from pre-digital users to digital native users where firms and customers are exposed to others [5, 6], and some firms, like banks, lack alignment with current relationship marketing strategies [7]. Other scholars look for the corporate brand perceptions through influencers in social media [8], typology of social media followers in brands [9], or the increased use of social media marketing to improve customer equity and purchase intention [10]. Besides, customer relationship capabilities and business performance [11], purchase intention via the mediation of social identification and satisfaction [12], to use of social media in brand building [13], or online corporate reputation in the banking sector [14]. Those studies have been based on the analysis of feelings, opinions, emotions, perceptions, and behaviours' influence on social media. These features are essential when the customer gets in the process of deciding about the company's products or services [15-17].

Although data analytics is a key to increase marketing communication effectiveness and knowing customers [18-20], the efficiency of marketing activities in several banks is low productivity [21], and digital strategy and brand building strategies in social media are limited or results do not clear. They could affect preferences, loyalty, and customer retention [22-26]. Social media marketing and competitive intelligence are not an active part of several banking strategies, but they can become tools for banks to consolidate their position in the market, understand the customer requirements and perceptions, identify the competitors' situation, and manage their knowledge [27-29]. In other words, opinions in social media and their orientation become a tool for decision-making in organizations like banks [30] or adopting a social media strategy to add value in their customer relationships [31, 32].

Banks in emerging markets have not consolidated social media marketing and competitive intelligence processes because they do not use several data from social media. However, some studies try to explain the relevance of social networks for global banks and several banks in emerging markets [33, 34], but platforms like Facebook have had better performance than Twitter or YouTube, because of the platform structure and not because of the banks' strategy in the social networks. Thus, what happens with the Twitter strategies of banks? Could social media affect bank profitability?

Our motivation is that the digital strategy of several banks could be limited. We propose a classification of banks based on their temporal interaction in Twitter as a proxy to understand their social media scheme and establish patterns that define visual analytics framework as part of their strategy. This paper expands the literature on banking brand strategy in a social media context, adding a view of acting on social networks in a data-driven framework and complimented by visual analytics based on data visualization. Namely, we contribute to the banking strategy in social media through the identification of small-scale temporal interactions, unlike other social networks like Facebook or Instagram that have most longer interacting periods. This paper analyses four banks' interactions in Colombia in social media and their effects on banking strategy, especially online customer relationships. We identified their effectiveness and fitness to interact with their customers using a Twitter dataset, where our results allow us to contribute technical and managerial recommendations for guiding strategies based on banking interactions on Twitter for customer acquisition and retention.

The paper is organized as follows. The first section describes the data-collection process and the research methods applied. A third section reports the results of our analyses and some discussion, and we close the paper with the major conclusions.

2. Methods

2.1. Data collection

This work used public data generated on Twitter®. We selected four banks with the highest level of assets and operations in the Colombian market to exemplify social media patterns in the banking sector (Bancolombia, Banco de Bogotá, Banco BBVA Colombia, and Banco Davivienda). The dataset refers to the Twitter interactions of the official accounts of these banks between 2017 and 2020. Due to the data volume and the variety of the topics, it was necessary to identify those subsets that may be of particular interest and focus the analysis on them.

The content of Twitter is highly dynamic. The topics' popularity increases and decreases rapidly in small-scale temporal interactions. Hashtags are useful for the analysis of the general dynamics of topics on the web. For this, hashtags are integrated into official accounts of Banco de Bogota, BBVA Colombia, and Bancolombia, while Banco Davivienda has two official accounts and two institutional hashtags. We analyse the tweets information sent by each official account (*TE*), the likes received (*LK*), and retweets generated (*RT)*. We considered only the own tweets; therefore, retweets made by official accounts are not part of the analysis. In this data collection, first, we directly incorporated customers of selected banks, and second, we developed an opinion mining to identify the banking interactions in Twitter and brand analytics.

The social media acts as a block, and, sometimes, there may be a diffusion before a particular text that dissipates over time; additionally, Twitter® tags allow identifying the trending topics that can be generated at a specific moment [35]. Sometimes, this diffusion processes can affect brand, products, or services, while in other cases, the diffusion process is an individual reaction that directs the information as a single comment within a defined variable. However, this diffusion can dissipate rapidly, but this evolution also required social reinforcement [36].

Consequently, this pattern will be relevant to identify because they build a strategy for the selected banks.

Thus, the information ecology in social media for the banking sector identifies user interaction patterns on Twitter® and enables defining the dynamics of populations and relationships with each other [37]. Likewise, information ecology can be vital for the banking strategy, more specifically to make it more agile and to mould it based on the dynamics of social media temporal interaction and adaptation to the evolution of customer preferences.

2.2. Model

The study of how opinions, perceptions, and feelings spread has been a central topic in social media because, first, perceptions could contribute to consumer engagement and relationship building [38], and second, social media adds more value than other channels for obtaining insights about products and services [39]. However, it is not clear if there is a contagion process where information flows between two agents' interaction in a neighbourhood or a contagion process where information requires an agent's neighbourhood. In social media, the continuous state of illness and recovery does not exist like in the traditional contagion SIR model that computes the theoretical number of people infected with a contagious illness in a closed population over time. Thus, how many people are susceptible S(t)? A social network like Twitter has random interactions with different penetration levels, and, in some cases, an agent may act as a super-spreader with the ability to infect many other agents or assume a peripheral role in the next interaction, even become isolated from the rest of the network [40-42].

Besides, social media interactions result from multiple contact sources where agents' opinions co-evolve temporarily with different results until dissipating. Thus, what kind of interactions do banks wait in social media? What kind of contagious properties prefer for their social media strategy? How many agents share the same opinion or feelings about some issues of the bank? What is the power of the neighbours?

We can talk about spontaneous support in banking cases because of small-scale temporal interactions, but the social media strategy can create different dynamics and opinion configurations. In simple contagion models, one exposure to a new state may be sufficient [43], while complex contagion models require social affirmation or reinforcement from multiple sources [33, 44, 45]. Even if there are few interactions, the complex contagion model accurately describes the spread of behaviours driven by online sharing [46]. First, because the social media interactions have a rapid spread, but a short amplification and they are fragile, especially some corporate Twitter accounts. Second, bank interactions in social media involved two or more agents. Third, few interactions can efficiently reach a consensus [47]. Fourth, the difference between contagion processes is that the probability of adoption depends on the number of exposures [48] because models of complex contagion often result in a discontinuous transition while the simple model in a continuous transition [49]. In consequence, interaction volatility creates results that deepen with features of each banking social media strategy.

Namely, the contagion results from interaction dynamics and the capacity of networks to amplify that interaction [50]. Thus, the result depends on the kind of populations, the agent's interaction with neighbours, the interplay between social consensus and collective behaviour to define social norms [51, 52], the emergence of consensus as a cooperative or competitive process [53], the network clustering, the network diameter, and the same complexity of network [44, 53].

Hence, information diffusion operates as a contagion process in a network, i.e., the information disseminated through an agent or group that can facilitate or restricts its progress but always defined as a dynamic process [54, 55]. However, agents can decide to transmit the information based on the results that other agents close to their neighbourhood have had [54]. In this case, first, information diffusion may be impaired because agents seek to interact with others who are equal to them and not allow another agent to decide to transmit the information [56]. Secondly, can also be a process when some agent assumed the risk of information disseminating, other agents do it, that is, everything arises from the agent expectations and their behavioural biases [57]. Third, it can be the result of direct effects that information may or may not have, since agents decide to transmit the information A depending on what they can obtain from it and, sometimes, the decision will be justified if the agent i has transmitted or not [56].

In this way, information diffusion can be justified based on what the nearest neighbouring agents do and the benefits they obtain from spreading the information (Fig. 1). It can assume that the agent i has d neighbours and a fraction p of its neighbours transmit the information A, and the part $(1-p)$ transmits the information B. Mathematically pd adopts A and $(1-p)d$ adopts B, then if the benefit for j of adopting A is pda and of adopting B is $(1-p)db$, A will be a better option if $pda \geq (1-p)db$. To transmit the information, the decision of agent j incorporates other considerations that require greater complexity beyond the benefit of doing so (e.g., additional incentives). Some agents do not transmit the information because there are many factors that they cannot assume or that outweigh the benefit of replicating, like the case of agents j_7 or j_8 (Fig. 1).

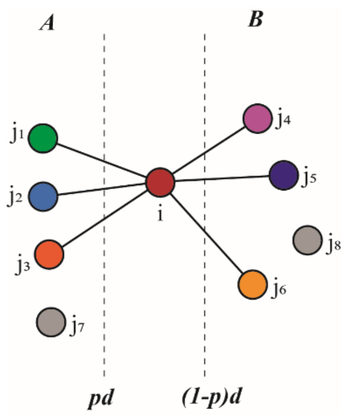

Fig. 1. Information diffusion of agent i.

All the agents j within a distanced could receive information from i and update their status as diffusor of information A or information B. If an agent j receives the information, he could diffuse it; otherwise, he simply does not diffuse it.

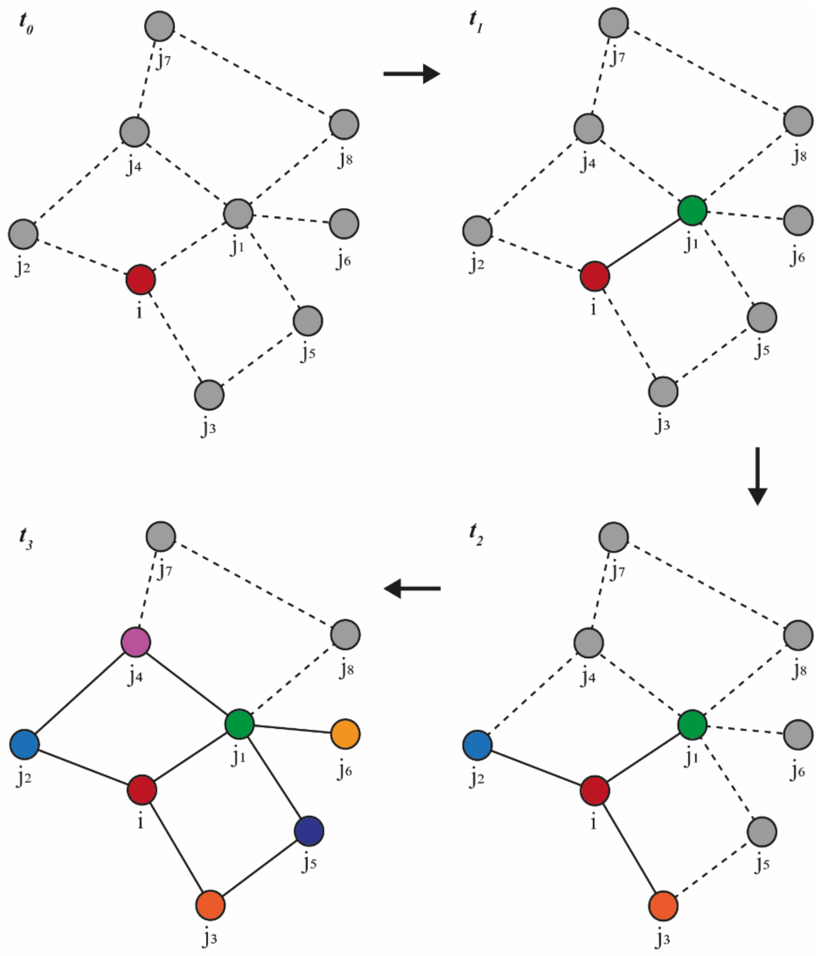

Fig. 2. Information diffusion in *t*.

From t_0 to t_3 information diffusion. Snapshots of the temporal evolution of the diffusion process (top, t_0 and t_1) and next period (bottom, t_2 and t_3) on a social media network. While in t_0 only the agent i have information, in t_1 the diffusion process started from the agent i to agent j_1. The population of $N = 8$ agents, where each agent starts in a different period. Grey nodes correspond to agents that do not diffuse the information in t that complemented with the dashed line. Colour nodes correspond to agents that diffuse the information in t (e.g., j_2, j_3), except the nodes that need another agent to diffuse the information (e.g., j_4, j_5, j_6). In t_3, agents j_7 and j_8 did not diffuse the information and finish the process, i.e., the process is finite.

Not always, first agents that propagate the information can influence the dissemination by other agents because the power of influence needs access to other easily influenced agents [58]. Namely, the diffusion process cannot be defined only in period t , but in an indefinite sequence of periods, $t = 0, 1, 2, 3, \ldots, n$, where

$t > 0$. In consequence, the information diffusion can be argued from the trajectory that results from successive random processes, since the position of an agent in period t depends only on its position at some previous period (e.g., $t - 1$), and some random variable that determines its direction and the length of each of its steps. This process also varies concerning the time when $t \to \infty$ because the number of diffusion possibilities increases (Fig. 2).

2.3. Analytical approach

To predict the social media contents, we introduce attributes and their entropy that is derived before and after of observation process. These attributes are given by:

$$H(Y) = -\sum_{y \in Y} p\,(y) log_2 p(y) \tag{1}$$

$$H(Y|X) = -\sum_{x \in X} p\,(x) \sum_{y \in Y} p\,(y|x) log_2 p(y|x) \tag{2}$$

If X is an attribute and Y is the class, Eq. (1) and (2) facilitate defining the entropy class before and after observing the attribute. The amount by which entropy decreases reflects the additional information provided by the attribute and called information gain, where each one is assigned a score based on the benefit obtained [59]. Additionally, a factor was assigned that measures like and retweets received as a proportion of tweets sent in a specific month. This value defined as the impact is given by:

$$Imp_i = \frac{likes_i + retweets_i}{tweets_i}, i = January, February, \ldots, n \tag{3}$$

In contrast with the relative impact of publications, we compared likes and retweets received each month as a proportion of the total likes and retweets received in the analysis period. This value is given by:

$$ImpR_i = \frac{likes_i + retweets_i}{\sum_i l\,ikes_i + retweets_i}, i = January, February, \ldots, n \tag{4}$$

For simplicity, in this paper, we choose the month as a time unit, but the analysis could be used in other time range, especially when the data traffic is higher than in this case.

3. Results

The simple count of tweets generated by each bank monthly presents a static behaviour except for interactions in some months by two official accounts of Banco Davivienda, and Bancolombia was the bank with the most continuity during 2017 (Fig. 3(a)). Additionally, the heat map gives us the relative impact of tweets sent by each bank in 2017 and identifies how scattered interactions of official accounts have been during the analysis period without defining a clear trend. However, months with F>0.75 facilitate the analysis because banks could concentrate on those months to identify patterns that help them define a digital strategy (Fig. 3(b)).

Additionally, we used a pre-processing algorithm to remove symbols, marks, and empty words (articles, pronouns, and prepositions) that could distort the use of words.

As well as lemmatization to reduce words to their root. In this case, we highlighted that the only account that focuses on aspects other than customer attention is the second account of Banco Davivienda that reduces the words dispersion and presents a better link with its marketing campaign words. In the same way, happens with hashtags visualization, where Davivenda's account shows an integration with them that directs it to have better precision in its social media strategy.

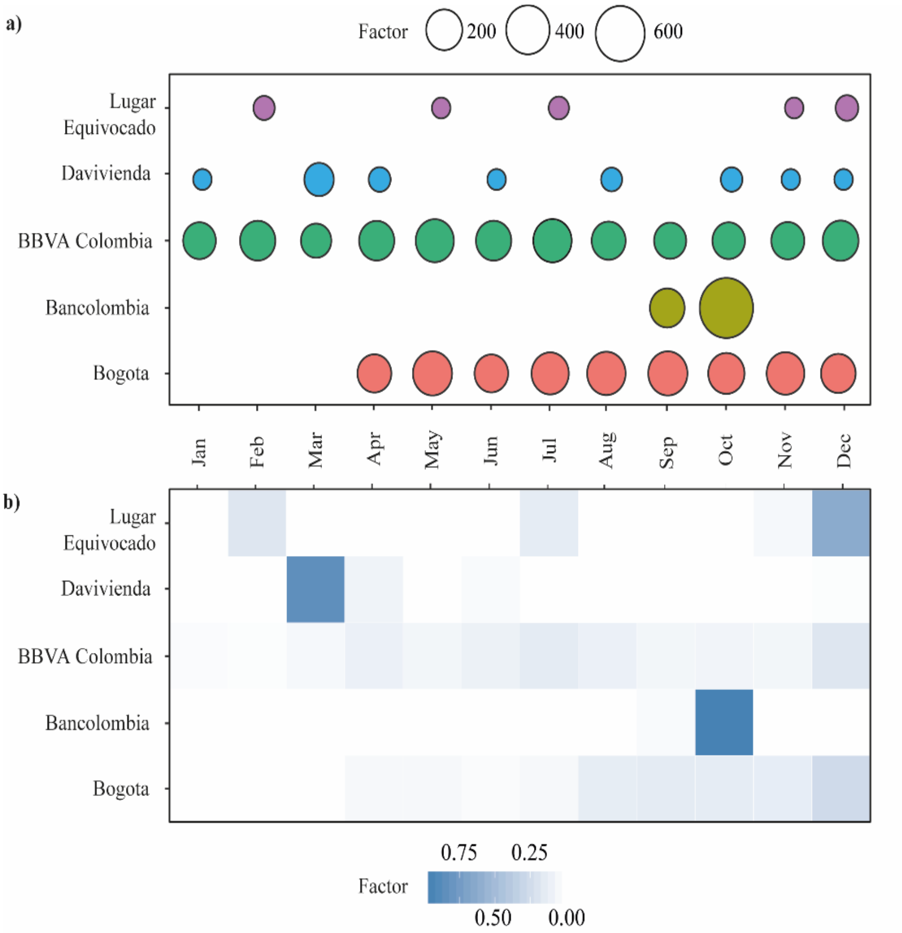

Fig. 3. Banks Interactions by Twitter during 2017.

The total tweets showed heterogeneous interactions without a clear strategy that banks could visualize. Fig. a) shows stationarity like a strategy by season for one bank (e.g., May: Mother's Day, July, Vacation, December Christmas), while Fig. b) confirms the dispersion of Twitter strategy.

Other banks visualize a set of words that identify interactions with their customers focused on services relationship, i.e., they seek to solve a particular customer problem through the public messages with words that concentrated this topic (e.g., number, account, send us, tell us, password, favour, request, message to name a few). Those results were similar during 2017, 2018 (an exception during the FIFA World Cup), and 2019. Those results were similar during 2017, 2018, and 2019, but during the FIFA World Cup 2018, several interactions concentrated on football marketing strategy gained relevance. The unusual pandemic year of 2020 shows a similar situation, especially with the word's heterogeneity with a defined minimum frequency (see comparison in Fig. 4). However, the posts' semantic changed to a more kindness interaction, principally by the responsibility of self-care and social distance to control the COVID-19.

The word visualization gives us an approximation to competitive intelligence because Banco de Bogotá, Bancolombia and BBVA Colombia are using their Twitter accounts as another customer relationship channel and not building their brand or building appropriation and consolidation strategy, i.e., a reactionary strategy [60]. Complementing the previous result, we incorporated bigrams as another data visualization tool that favours the predictive analytics construction, i.e., data visualization optimization or a high-performance data visualization environment [61] that confirms that the social media strategy focuses on customer problems.

Additionally, these results can confront with heatmaps to visualize the degree of similarity between different tweets. The Euclidean distance matrix allows grouping diverse conversation topics between tweets, where we selected the number of groups applying the Elbow method to each bank. As a result, clusters predominantly yellow correspond to the tweets group that refers to a specific topic while the clusters blue corresponds to the general that refers to the same topic as other tweets.

Clusters of 2018 show that heat maps of Banco de Bogota (Fig. 4a), Bancolombia (Fig. 4b), and BBVA Colombia ((Fig. 4c) are close to having a general similarity in referred topics about customer problems during both periods. Banco Davivienda presents specific topics about brand building because the common words are the name of services and to a lesser extent to customer service issues and its scale is between 0.0 to 0.6 (Fig. 4d). Besides, there a homogeneity in the cluster sizes while the Banco de Bogota, Bancolombia, and BBVA Colombia are heterogeneous, there are more words with a defined minimum frequency with small scale, i.e., 0.0 to 0.2. In clusters of 2020, the COVID-19 and online security topics increased their relevance. The general word clusters (blue) reduced their participation possibly by the increase in the number of interactions during 2020 because the words are like 2017 and 2018.

With these visualizations, we identified results of social media strategy and interactions between banks and users. Banco Davivienda has achieved a deep brand strategy on Twitter, and we confirmed this with the hashtag strategy where there is no excessive expansion of hashtags but concentrates on a few with important impact factor. In the case of BBVA Colombia, hashtags concentration is a result of a sponsorship campaign.

However, using individual words and their edges from networks, we confirmed that situation partially because network topology for the four banks had similar conditions (Fig. 5). The NGram topologies present a word network for each bank that differentiates interactions and word that centralizes in a large proportion of those interactions. Patterns in the four banks refer to send (example in Spanish: *envianos, dm, via*). This pattern confirms that interactions seek to solve customer services problem. The Banco Davivienda case shows two words that confirm the hypothesis about brand building. The second word with a great centrality is a product name of money transfer service in social media platforms.

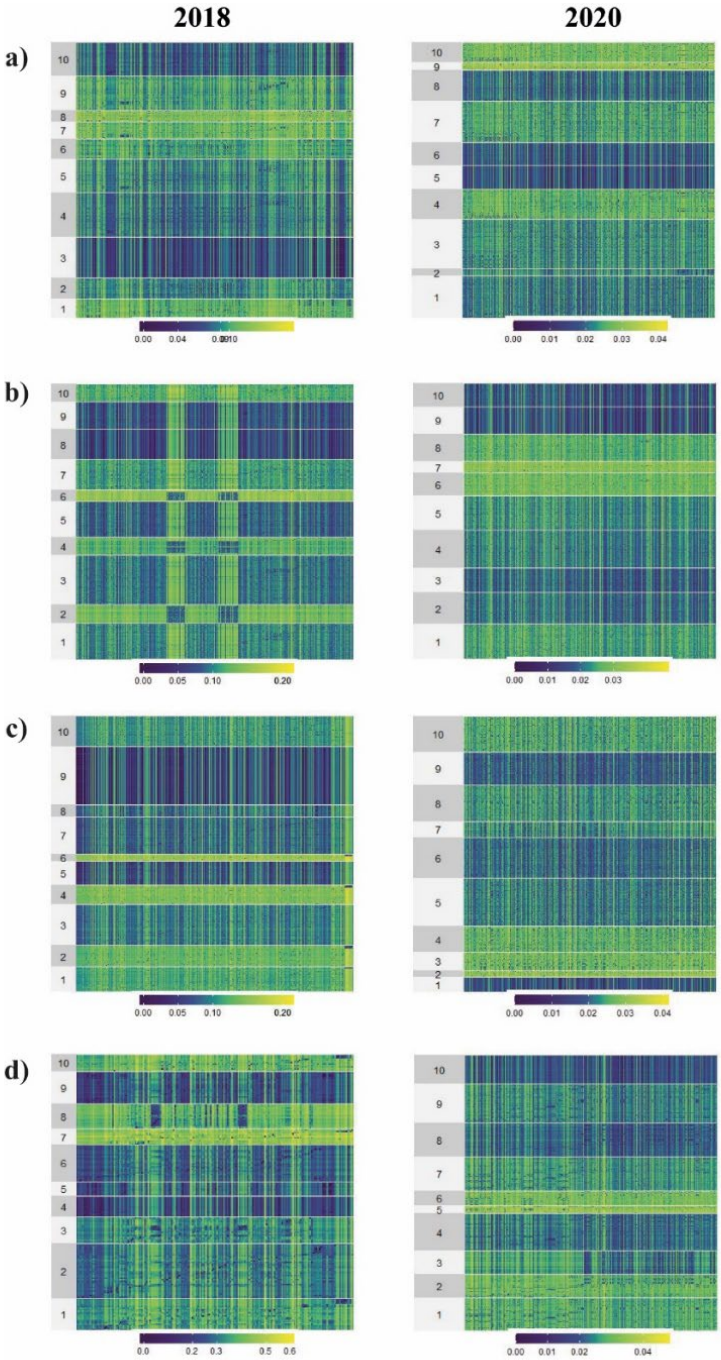

Fig. 4. Twitter Comparison Heatmaps 2018 versus 2020.

a) Banco de Bogotá, b) Bancolombia, c) BBVA Colombia, d) Banco Davivienda.

Clustering reveals patterns in the data especially, the heterogeneity of the three top shows there are more words with a defined minimum frequency. The bottom heatmap reflected homogeneity, principally by the frequency of the services' name and their word's interactions related to marketing strategy.

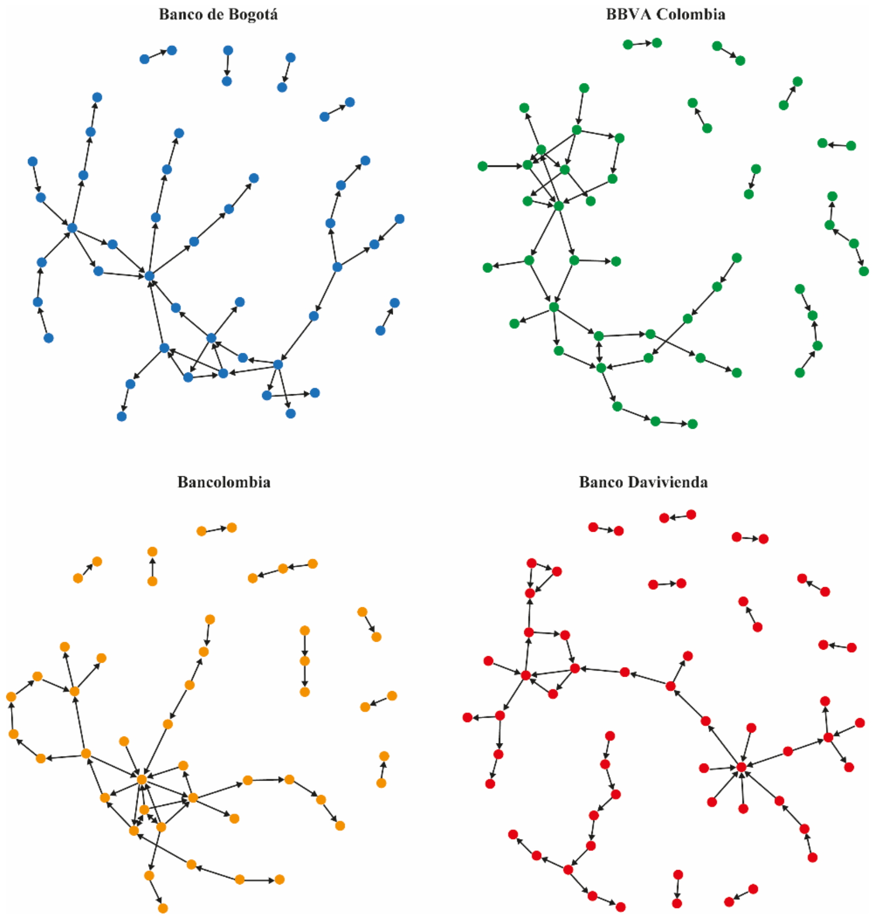

Fig. 5. N-Gram Topologies 2018.

Topologies were characterized by a central network and some single interactions between two words and a few cases between three or four (nodes represent words and edges represent the direction of word interaction). The bottom-right network presents a second network that reflected a different interaction type to the customer relationship that is a common factor in the other three networks.

In 2020, we perform a sentiment analysis through the chains of messages. The scale is a coefficient between (-1, 1), where -1 is negative, 0 is neutral, and 1 is positive. Fig. 6 shows that tweets trended to a neutral position, but in some cases, the density was more relevance on the negative side than the positive side of messages for Banco Davivienda, BBVA, Bancolombia, and Banco de Bogotá, respectively (Fig. 6).

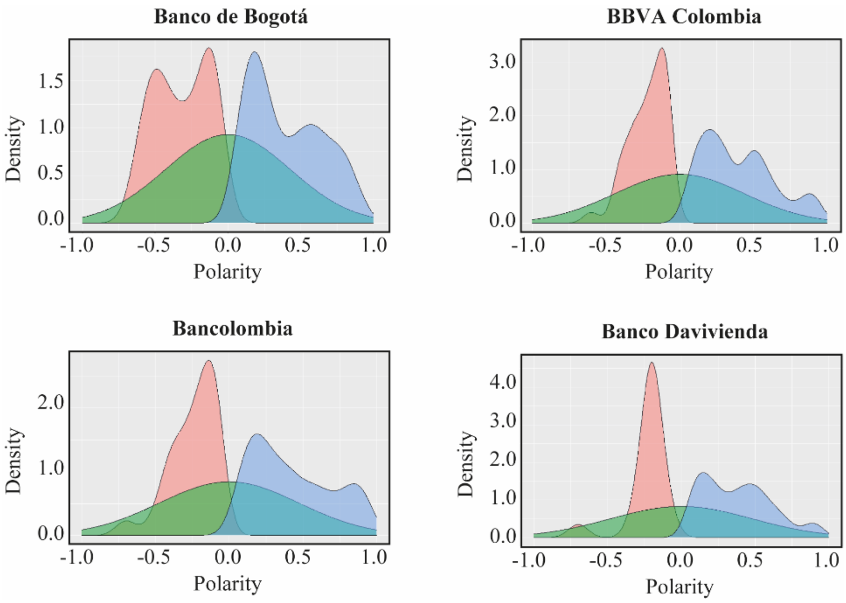

Fig. 6. Sentiment Analysis 2020.
(Red represents the negative factor, blue represents the positive factor, and green the neutral factor.)

4. Discussion

In this work, we have proposed a generalized model of information diffusion processes in social media as a mechanism to identify the digital strategy of several banks in Colombia, that a simple contagion mechanism does not trigger a cascading contagion. Our results give rise to diverse interpretations about interactions between customers and banks with continuous and discontinuous transitions because customer problems are the most relevant topic. That topic affects the continuity of the information diffusion process because it is an interaction between bank and customer, but on some occasions, the negative sentiment that results from customer problems increased the diffusion process. Specifically, this situation becomes a critical point for digital strategy.

For information that is less sensitive as the customer problems, certain environments may be more useful to launch of specific digital strategy in Twitter by banks. If users interact with banks trough a brand strategy, people may be able to share, for example, the message of the day or other messages with a larger number of their social contacts. However, the marketing strategy must capture the attention of customers with different preferences, activities, backgrounds, and online time to obtain opportunities to transmit information. Thus, banks need to reduce online weak ties with their customers because those ties would be fewer effective channels to digital strategy, and the investment net effect would tend to 0 or negative values.

Besides, when we check several months during the analysis period, we identify some features to discuss. First, we showed that the model identifies words that concentrate on customer services, achieving an accuracy of 99.9% when considering more than 15,000 tweets per year with a relevant increase during 2020 (almost 20,000). Secondly, we showed that events like the FIFA World Cup in 2018 increased the interactions between banks and customers, especially with marketing and branding messages. Crucially, these interactions can be inputted as a successful strategy in social media by banks. However, after the World Cup 2018 finished, the customer service interactions and the negative feelings increased dramatically with greater information diffusion.

Third, we compared the number of tweets during the pandemic of COVID-19 and found to message interact between marketing strategy and customer services increased indistinctly because restrictions and lockdown processes affected the service in the branch network and some customers used with more frequency the online platforms. Given this, the increase of customer claims could be used to identify the online traffic and the most frequent problems, where banks could reorientate their digital strategies used visual analytics.

Lastly, the marketing strategy during COVID-19 had two topics: online security and recommendations against COVID-19 that did not represent a brand consolidation because banks are showing two problems. The first one shows the weakness of cybersecurity during a period that customers increased the use of online platforms (negative message) and the second one is a generic strategy that diverse local and global institutions of several sectors did it during 2020. In some cases, greater information diffusion but not a successful digital strategy.

In summary, banks need two Twitter accounts, one for digital strategy and the other for customer services like Banco Davivienda has implemented with relative success according to the visual results. All banks need two different accounts. Although it is the same company, needs those channels to allow driving the marketing strategy (products and services) and customer relationship because in the same account not exist brand communication effectiveness with customers. Also, the business performance measurement of only one account affects the social media strategy.

5. Conclusions

Our work shows that Colombian banks have not managed an articulate social media strategy because they do not present a specific line to understand the information that they try to transmit to their customers. From data and customer interaction in social networks, Colombian banks use social media as a form of information disclosure, but none has built a structure that allows them to improve their market position. They did not use the consumer small-scale temporal interaction to get corrective actions to improve the quality of service when difficulties arise. But some banks try to develop a brand strategy and, in some cases, facilitate to develop strategies to offer products through social media. However, banks on Twitter need a small-scale temporalities strategy because users interact rapidly, and their decision-making process only takes a small-time before to check another tweet. This conclusion is exclusively for Twitter because other social media platforms like Facebook, Instagram or LinkedIn have most longer interacting periods. Consequently, the visualization methodology becomes a tool for strategy control indicators. As a result, the words' heterogeneity found despite the adjustments made with our method, except for the case of Banco Davivienda, which is close to having the most appropriate scenario to use social media as a platform to launch a product or a marketing campaign. The other banks' social media platform becomes repetitive concerning customer problems.

In summary, this paper serves to identify that information is influencing or not in brand building and customer perception. Secondly, to build knowledge that is fundamental in the definition of social media strategies for banking. Third, to identify banks' appearance in networks and the impact of investments that banks make in their digital strategy trough data visualization and visual analytics tools. Fourth, banks have created a digital structure to develop a brand-building strategy, but in some cases, the investment does not have an attractive yield because some banks do not have a specific strategy to apply on Twitter. Fifth, banks do not have the fitness to manage a social media strategy in small-scale temporal interactions. Sixth, the visual analytics identified if security problems with the customer information could be because the most representative words are the dynamic password, virtual office, credit card, or id. Although banks solicit this information through private interaction, preliminary tests have been made with regular expressions trying to find the number over replying to chains of messages, but results are not conclusive.

Eventually, we expect to implement this methodology with other Latin American banks because patterns define those banks to strength social media strategies need to adopt visual analytics, best-trained models for image and audio analytics, i.e., great infrastructure investments in cloud computing technologies. Thus, banks need to try a new stage in social media strategies from a single message to data visualization-driven tools because the digital transformation is a reality, and some banks use and invest in social media, but they do not harness the data resources. Further studies may be needed to confirm the effect of the digital strategy of banks on Twitter and other social networks, especially the network topology and heterogeneity.

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