

İstanbul İktisat Dergisi Istanbul Journal of Economics

Research Article

Open Access

A Comparative Analysis of Brands' Social Media Messages before, during and after the Pandemic



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Abstract

This research's goal is to explore the changes in social media marketing communication of national and international brands operating in Turkey by comparing three distinct periods, namely, prior to, during, and after the COVID-19 global pandemic, by implementing text mining techniques to certain brands' posts on the X platform. We used the structural topic model (STM), sentiment analysis, chi-squared analysis, and word frequency. First, we identify business-related topics such as communication campaigns, online transactions, and mobile banking as common themes across the years under investigation. In addition, brands include societal events such as special days, national achievements, or catastrophic natural disasters such as earthquakes or massive forest fires in their social media posts as a means of demonstrating solidarity with society. Then, using the NRC Word-Emotion Association Lexicon, we compared the sentiments of the business-related topics. The results indicate that the emotional variation of marketing messages did not present statistically significant changes irrespective of the period analysed ($p = 0.1229$ and 0.149). On the other hand, emotional variation in digitalisation-related content varied significantly depending on the investigated periods' circumstances ($p = 0.0019$). Moreover, anticipation, joy, and trust are prominent emotions in brands' social media messages irrespective of context-dependent circumstances, whereas others like fear, surprise, anger, disgust, and sadness change variations depending on the context. Furthermore, the results indicate that it is critical to mention continuity and hope in social media messages and engage the community during crisis times.

Keywords

COVID-19 • text mining • marketing communication • social media • sentiment analysis

Jel Codes

M30, M31



Citation: Cerit, M. M. & Karaosmanoğlu, E. (2026). A comparative analysis of brands' social media messages before, during and after the pandemic. *İstanbul İktisat Dergisi–Istanbul Journal of Economics*, 76(1), 127-148. <https://doi.org/10.26650/ISTJECON2025-1793138>

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 2026. Cerit, M. M. & Karaosmanoğlu, E.

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A Comparative Analysis of Brands' Social Media Messages before, during and after the Pandemic

Various research in the marketing literature used text analyses to gain valuable insights regarding, for instance, marketing communication (Mangiò et al., 2021; Farmaki et al., 2022; Pezoa-Fuentes et al., 2023) or consumer behaviour (Yousefi et al., 2020; Oh & Yi, 2022; Naurin & Michel, 2023; Sungwon et al., 2023) during the COVID-19 pandemic (hereinafter, the pandemic). Mangiò et al. (2021) identified that brands used ethical and societal discourse throughout the global pandemic by examining social media posts through applying specific text mining tools. Likewise, Hesse et al. (2021) reported that automated text mining applications are capable of identifying the social media posts that are specifically related to the pandemic.

Nonetheless, in spite of the plethora of research investigating user-created content on social media (Yousefi et al., 2020; Oh & Yi, 2022; Naurin & Michel, 2023), to the best of our knowledge, the literature remains deficient in comparative evidence on the application of text mining tools to investigate the progression of brands' messages across specific temporal phases: prior to, during, and after the pandemic. The importance of this evidence is twofold: first, the pandemic represented a comparatively exceptional form of crisis that affected various organisations; second, it is likely that society will confront such devastating crises in the future. Thus, the examination of pandemic-centred communication in social media might serve as a guide for marketing practitioners to use during likely crises in the future (Hesse et al., 2021). Likewise, the literature points out the importance of investigation communication prior to, during, and after the pandemic, with the aim of determining to what extent pandemic-related social media content varied from that of other topics (Scheiwiller & Zizka, 2021). Similarly, previous research has pointed out the importance of conducting research covering these three consecutive years to reveal changes in corporate communication strategies (Kharbat et al., 2024). It is extremely challenging to construct the right communication messages for consumers in unprecedented times (Li & McCrary, 2022) because "marketing is a contextual discipline" (Sheth, 2022), and it cannot be regarded as detached from the contextual circumstances. Moreover, studies dealing with emerging economies are rare compared to the number of studies conducted in Western countries during the pandemic. However, it is argued that a comprehensive understanding of coping strategies for potential crises, such as the pandemic, is necessary in a business context (Uzkurt et al., 2023). Adopting an exploratory research approach, this paper aims to contribute to these gaps by examining the brand messages posted on social media throughout three years, covering before, during, and after the pandemic.

The purpose of this paper is to analyse social media communications of domestic and international companies operating in Turkey. It employs automated text analysis techniques to examine the content of brand messages published on X (previously called Twitter) pre-, during, and post-pandemic (2019-2022). The objective was to determine the degree of changes in brand discourses throughout the investigated period. To do that we first extracted our data from X using the R programming language. After conducting data preparation procedures, we proceeded to implement structural topic modelling (STM) on the messages of brands. STM provides us with certain topics and changes in these topics throughout the relevant years (2019-2022). We have investigated business-related topics in greater depth using sentiment analysis to discern the underlying emotional patterns. As a final stage, we examined the wording responsible for the identified emotional shifts in the investigated topics. Our results shed light on how marketing messages

can be altered depending on the circumstances of social crises. In addition, we have outlined the salient emotions that may emerge within brand messages in the midst of such crises.

This paper is outlined as follows. First, we highlight the importance of brand communication via social media. Later, we explain the data collection process and elaborate on data preparation. Thereafter, we proceed to the emotional analysis after the STM analysis. As the final step of the analysis, we examine the wording employed in brand communications. We conclude with a discussion on brand communications in crisis times that corroborates the results of our research. Limitations and future research directions are also presented.

Importance of Brand Communication via Social Media

Social media is one of the most significant tools used by marketing practitioners in terms of conducting marketing communication (Kusumasondjaja, 2018). Social media platforms facilitate communication among consumers as well as consumer-company interactions (Batra & Keller, 2016; Labrecque, 2014). For instance, responding to consumers' complaints on social media usually contributes to the customer-firm relationship and has the potential to generate more favourable online posts from current and potential consumers (Ma et al., 2015). These platforms function as a central hub for the promotion of companies' goods and services, facilitating interactive engagement between marketers and consumers (Ismail, 2017). Essentially, they provide new ways for firms and customers to interact with one another so that consumers' evaluations of the social media content created by firms directly affect brand equity-related constructs such as brand awareness (Schivinski & Dabrowski, 2015), brand loyalty, and brand consciousness (Ismail, 2017). Brand equity further enhances the probability of marketing communication effectiveness (Yoo et al., 2000). Moreover, social media brand communication identifies the capability of brands to distribute information and respond to consumers' requirements (Zha et al., 2023), which results in positive social media brand engagement (Gómez et al., 2019). More broadly, it is discussed that social media has the potential to influence the following creating awareness and salience, creating brand imagery and personality, building trust, eliciting emotions, and connecting people (Batra & Keller, 2016).

Brand communication via social media preserved its importance even during the pandemic. According to industrial research, spending on social media marketing increased by approximately 74% during the pandemic, accounting for a significant portion of total marketing budgets (Moorman, 2020). The pandemic-induced circumstances were responsible for these developments because, on the one hand, the conditions hindered many communication channels such as outdoor activities or industrial exhibitions, and on the other hand, brands had to remain relevant to consumers during such ambiguous times (Palton, 2020). For instance, the research shows that brands designed specific communication patterns in social media to reflect their solidarity with the public through socially responsible behaviours such as transferring funds, goods, or services to certain institutions; to present their support in a physical or psychological way, such as through promotional offers, mentioning entertainment, or showing optimism and humour; and to gain credibility by educating society about pandemic-induced circumstances such as governmental policies, regulations, and restrictions (Hesse et al., 2021). The placement of the pandemic in brands' social media messages also influenced consumers' online engagement behaviour during the pandemic. Specifically, implicit mention of the pandemic in social media brand messages positively influences online engagement behaviour, whereas explicit mention does not yield such a significant effect (Kleer & Kunz, 2023). Furthermore, social media played a crucial role throughout the pandemic by encouraging pro-social behaviour by using influencers. It also provided regular updates to the public regarding the reopening process (Mele et al., 2023).

Data Collection

We chose the X platform for use as a data source since it is used as an integrated marketing communications platform to communicate with and inform actual and prospective consumers (Liu, 2020). X reaches several users. According to the recent statistics, X is the third most used social media platform in Turkey with over 20 million accounts, while around 13 million of these users are active ones (Twitter Users, Stats, Data & Trends, 2023). The report shows that X's potential ad reach in Turkey is around 2.1 million users (Kemp, 2024). The majority of national and international brands have active formal X accounts through which they communicate with their actual and potential customers. Compared to other platforms such as Facebook or Instagram, brands preferred X as a tool to disseminate mostly informative messages (Kusumasondjaja, 2018). The research shows that organisations used X to inform the public about the developments related to the crisis during the pandemic (Dhar & Bose, 2022). Since it provided free access to the publicly available data, we used the X API¹ to obtain the brands' tweets. We ensured data access by applying for an X development account, which granted authorisation to access publicly available tweets. We used R to collect and analyse the tweets we gathered.

The lists of three independent institutions (Brand Finance, Capital, and Ipsos) served as the sampling source to identify the brands to investigate. While some brands appear in two or three separate lists, others are only available in a single list. There were 124 individual brands. We extracted football clubs' and Istanbul Stock Exchange's social media accounts from the sample due to noncompliance between the contents shared on X and the research objectives. Those brands that lacked an official X account and did not actively use the account were also eliminated, leaving 85 unique brands on the final list. Only the tweets in Turkish are used so that the final dataset consists of 22803 tweets and associated metrics, including the number of favourites, account creation date, account name, and the number of retweets. During the analysis, we focused solely on the tweets posted directly by the selected brands, excluding any retweets from either the brands or other users.

Data Preprocessing

After authorisation to use the API, we used R software to extract the desired tweets of brands by applying *twitterR* (Gentry, 2022) and *retweet* (Kearney et al., 2024) packages. Following the collection of tweets, we performed Berger et al.'s (2020) specific text-preprocessing steps, such as the removal of punctuations, digits, and stop words. To eliminate stop words, the "*stopwords*" package in R was used. However, since stop-word packages for Turkish are not as capable as enough to eliminate certain unnecessary words, we also used regular expressions (regex) in the R script to target and remove specific meaningless words that would otherwise contribute to the noise of the entire dataset. Regex enables researchers to recognise a specific pattern in any text. Using R's regular expressions, we eliminated, for instance, all words with three or fewer letters. These words could be conjunctions like "ile" ("with" in English) or "de/da" ("also" in English) or pronouns like "ben" ("I" in English). In certain instances, removing punctuation, extra white spaces, or the previously mentioned words resulted in a collection of letters that only resembled a word. To target and remove these words, we used a regex that matched words with three or more consecutive vowels, which is not a suitable string for the grammar of Turkish words. Similarly, we eliminated the words with five or more consecutive consonants. Lastly, we omitted the brand names in the tweets to hinder the appearance of brand names in the analysis unit.

¹Twitter API was free of charges for academic usage before it was converted into X

Upon completion of data preprocessing, the full dataset was divided into three temporal intervals. On March 11, 2020, the pandemic was officially declared in Türkiye. This date functions as our reference point. We designated the interval from March 11, 2019, to March 11, 2020, as "prior to the pandemic" and the duration from March 11, 2020, to March 11, 2021, as "during the pandemic". The period from March 11, 2021, to March 11, 2022, was designated as "post-pandemic." Prior to the pandemic, the brands in the sample generated 5377 tweets; however, during the pandemic, they tweeted 7406 times. Conversely, the aggregate number of tweets postpandemic amounted to 10020 (see Table 1). After preparing the data for analysis, we initially employed the structural topic model to discern the primary issues addressed over the years under review. We subsequently identified certain issues closely associated with marketing themes and conducted a sentiment analysis on these topics to elucidate the evolution of their emotive motivations throughout the specified years. Subsequently, we undertook an inquiry into the factors responsible for the alterations in the predominant emotions linked to these prevalent subjects.

Table 1*Inspected time periods*

Periods	Time Interval	Number of tweets posted
Before the Pandemic	11.03.2019–10.03.2020	5.377
During the Pandemic	11.03.2020–10.03.2021	7.406
After the Pandemic	11.03.2021–10.03.2022	10.020

Structural Topic Model

As common text analysis techniques, topic model techniques can be used to automatically identify the hidden topics in a relatively significant amount of text by associating the words in the text with one another (Berger et al., 2020). Their diagnostic ability is quite satisfactory in terms of finding related terms in the text data (Alantari et al., 2022). The Structural Topic Model (STM), which is distinct from other topic models such as the Latent Dirichlet Allocation (LDA) (Blei et al., 2003) and the Correlated Topic Model (Blei & Lafferty, 2007), incorporates the metadata of the complete dataset into its analysis process. The method enables researchers to establish associations between the metadata and the data. Using STM, researchers estimate the relationship between the topics identified and the document metadata, which consists of uncovering the subjects addressed in the documents (Roberts et al., 2019).

This research used STM to determine the changes in the frequently discussed topics in brands' social media posts over a three-year period. Prior to the STM analysis, we aggregated tweets shared on the same day throughout a 3-year span and classified them into specific temporal phases: pre-COVID, during COVID, and post-COVID. Consequently, we established two subsets: one consisting of tweets disseminated prior to and during the pandemic, and the other encompassing tweets released during and after the pandemic. As a result, binary comparisons could be performed within each subset. Given our primary objective to ascertain the evolution of brands' marketing discourse on social media during the pandemic relative to the years before and after, we performed a comparative analysis of these two time frames against the pandemic year. Given our principal aim to ascertain the evolution of brands' marketing discourse on social media during the pandemic relative to the years before and after, we performed a comparative analysis of these two time frames against the pandemic year. To operationalise the STM, we determined the precise number of topics to be recognised, ranging from 5 to 25, based on the interpretability of each topic. Ultimately, we concluded that seven topics adequately encapsulate all themes included in tweets disseminated from before to during

the pandemic, whereas twelve topics constitute the optimal quantity for those shared from during to after the pandemic.

Before and During the Pandemic

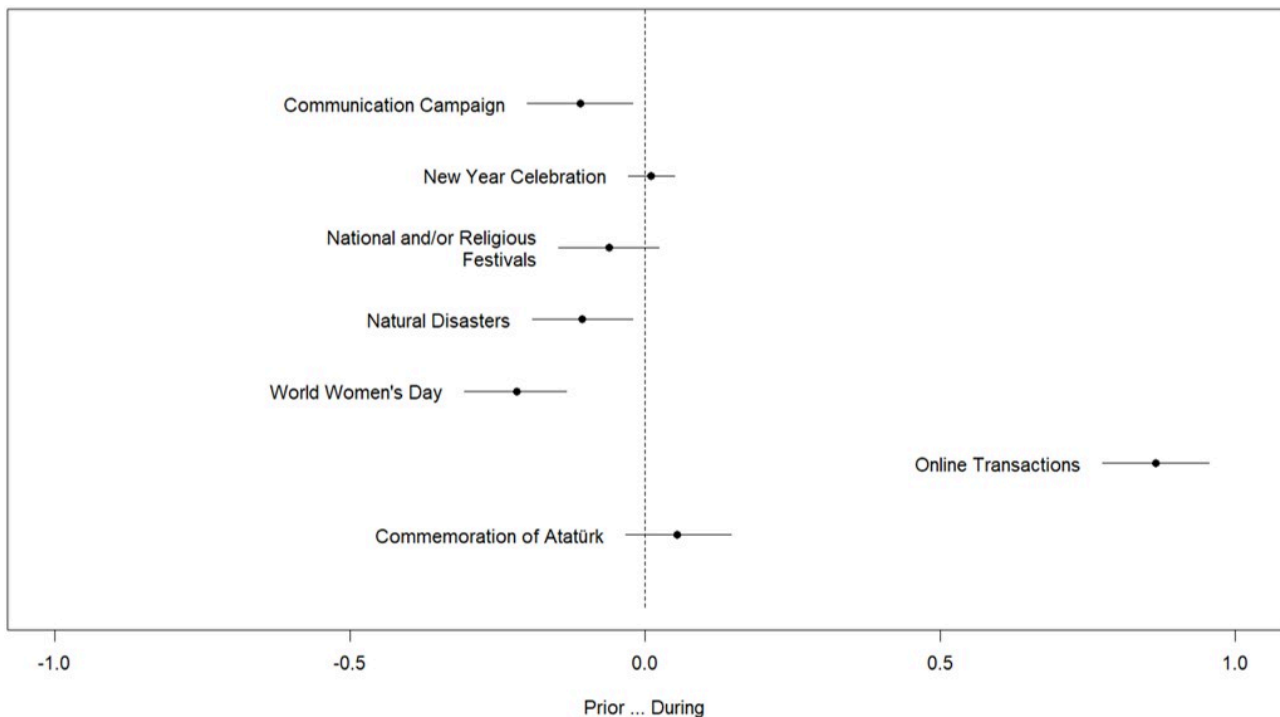
As previously stated, we have determined that seven topics represent the optimal quantity, encapsulating all the distinct themes that evolved in the period preceding and during the pandemic. (Table 2) compiles these issues together. The table displays the subjects represented by the 10 most frequently occurring words within each topic. These representative words are the instances that remained from the initial data preprocessing steps, as elaborated on previously. On the basis of the qualitative assessment of the word groups, the topics are labelled as follows: "communication campaigns," "earthquake," "online transactions," "the New Year celebration," "national and/or religious festivals," "International Women's Day," and "Commemoration of Mustafa Kemal Atatürk," the founder of the Republic of Türkiye. Following the identification of topic names, we have consolidated particular topics into comprehensive categories, such as marketing messages, solidarity, digitalisation, and messages of special days.

Table 2

Identified topics in brands' social media discussed before and during the pandemic

Comprehensive Category	Name of the Topic	Top 10 Representative Words
Digitalisation	Online Transactions	coronavirus, covid, digit, house, social, support, timeframe, todays, transactions, ziraat bank
Marketing Messages	Communication Campaigns	award-winning, catch, competition, country, design, even, house, practical, starting, students
Solidarity	Earthquake	citizen, customer, earthquake, emergency, experienced, existing, get well, life, mercy, region
Special Day(s)	International Women's Day	day, life, march, today, violence, woman, women, women's property, world
	National and Religious Festival Celebrations	festival, full, happy, happiness, healthy, peaceful, relatives, success, wish, year
	Commemoration of Mustafa Kemal Atatürk	atatürk, commemorate, kemal, leader, may, mustafa, respect, thankfulness, war veteran
	New Year Celebration	december, effective, magazine, new year, obstacle, simple, sleep, small, year

The primary distinction of STM from other topic models is its capability to enable researchers to assess the relationship between topics and metadata. An important aim of our research is to track the evolution of brand discourse over time, with the year of the pandemic serving as a point of reference. [Figure 1] illustrates the link between the specified topics and the analysed timeframes. The majority of texts of the pandemic have incorporated terminology related to online transactions. Our finding shows that brands have conveyed messages to inform consumers about the ease of managing transactions using mobile applications or websites throughout the pandemic. Moreover, the significance of the communication campaigns diminished during the pandemic relative to the pre-pandemic period. Throughout the two-year period, the communication campaigns have maintained a relatively minimal load. Additionally, brands have consistently exhibited awareness of social events, encompassing natural disasters, exemplified by the topic "Earthquake", and significant occasions, represented by "International Women's Day", "New Year", "Greeting Message for the Festival", and "Commemoration of Atatürk."

Figure 1*STM output for the periods before and during the pandemic*

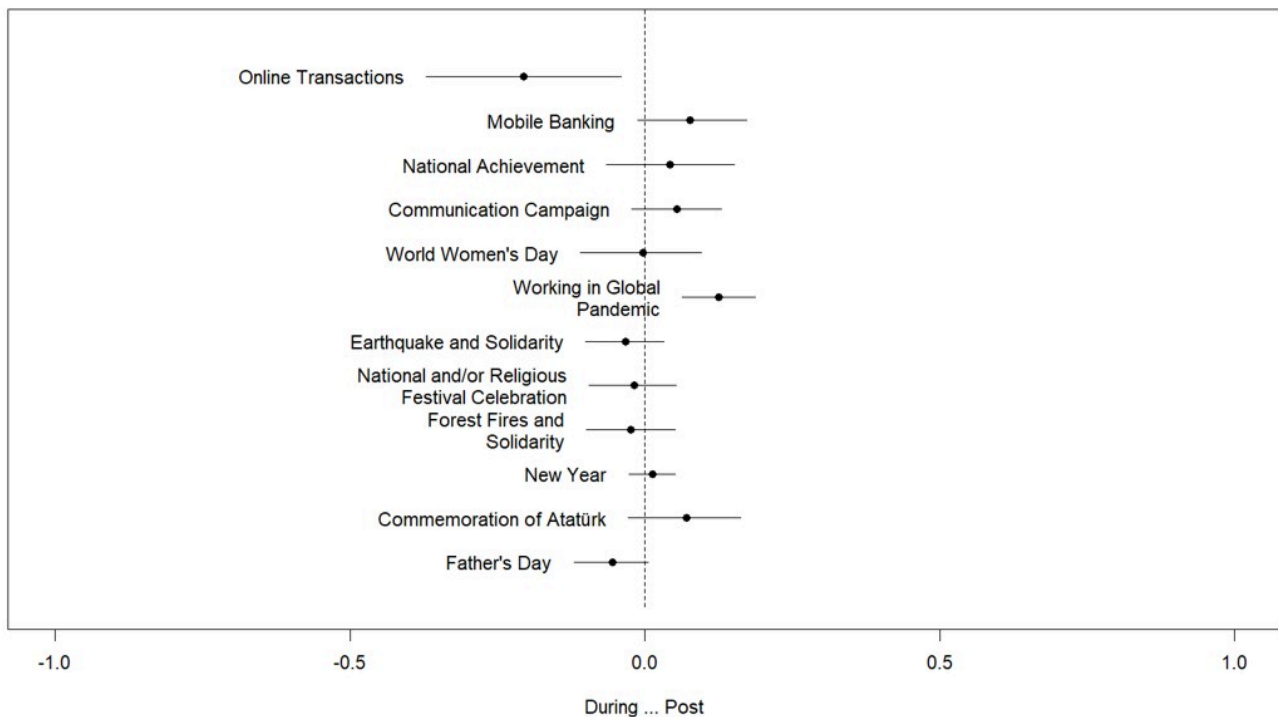
During and After the Pandemic

As previously stated, after multiple experiments, we determined that 12 topics represent the optimal quantity of unique topics discussed across brands' X accounts during the pandemic and post-pandemic periods. Table (Table3) illustrates the topics identified throughout this timeframe. The pandemic is directly associated with the topics of "online transactions" and "mobile banking," which were prevalent during that period. These were categorised under "digitalisation." The topic of "International Women's Day" is among the most prevalent at this time. Other topics include "National and Religious Festival Celebration," "the New Year Celebration," "Fathers' Day," and "Commemoration of Mustafa Kemal Atatürk." We have grouped these topics under "Messages covering Special Day(s)," which illustrates the sensitivity of brands to special days. Türkiye had to contend with forest fires in summer 2021, and we saw that the brands were sensitive to this calamity, as seen in the topic labelled as "forest fires." "Earthquake" is another identified topic similar to the previous time. We have grouped these two topics under the "solidarity" category. The last three identified topics are "national achievement in Olympic games," "seasonal communication campaigns," and "working conditions during the pandemic" categorised under "National Achievement," "Marketing Messages," and "Working Conditions during the Pandemic," respectively.

Table 3*Identified topics in brands' social media discussed during and after the pandemic*

Comprehensive Category	Name of the Topic	Top Representative Words
Digitalisation	Online Transactions	digit, easy, hour, long, mobile, money, payment, today, trust, Türkiye
	Mobile Banking	banking, covid, days, house, may, mobile, payment, term, transactions, ziraat bank
National Achievement	National Achievement in the Olympic Games	athlete, being, congratulations, europe, games, national, olympic, pride, sponsor, tokio
Marketing Messages	Seasonal Communication Campaigns	autumn, autumn-winter, beautiful, collection, missing, October, opportunity, season, September, you
Messages covering Special Day(s)	International Women's Day	directed, generation, march, November, today, violence, woman, women, world
	National and Religious Festival Celebrations	festival, full, happy, healthy, peaceful, relative, relatives, wish
	New Year Celebration	december, house, legend, new year, relatives, relatives, website, year
	Father's Day	day, father, future, happy, June, long, love, today, trust, world
Solidarity	Commemoration of Mustafa Kemal Atatürk	atatürk, commemorate, kemal, may, mustafa, respect, respect, war veteran
	Earthquake	communication, customer, earthquake, emergency, free, need, needs, present, region, talk
	Forest Fires	affected, august, citizen, coming, experienced, forest, getting well, life, mercy, sadness
Working Conditions during the Pandemic	Working Conditions during the Pandemic	april, coronavirus, days, daytime, employee, health, night, pandemic, term, vacation

Through an investigation of the metadata-topic relation in STM, we investigated the variations in topic proportions from the pandemic period to the post-pandemic phase, following the labelling and categorisation of the detected topics. [Figure 2] illustrates this association. Initially, we noted that financial institutions were increasingly using X to enhance the accessibility of online financial operations. The relative significance of these messages has become increasingly obvious, particularly following the global pandemic, whereas the relative importance of online transactions has reduced. Moreover, the significance of the communication campaigns escalated postpandemic compared to the pandemic period, as illustrated in [Figure 2];. Moreover, corporations often referenced working conditions during the pandemic and expressed their respect to employees who sustained their missions despite health risks.

Figure 2*STM output for the periods during and after the pandemic*

Examination of the Emotion-based Patterns of the Specific Topics

In the subsequent phase, we assessed the overall emotions associated with certain themes and indicated how these feelings fluctuated during the years in question. To achieve this, we utilised the Turkish version of the NRC Word-Emotion Association Lexicon (Mohammad & Turmey, 2013), comprising 13872 words classified by two sentiments and eight emotions: positive, negative, trust, surprise, fear, anticipation, joy, anger, disgust, and sadness. The preliminary research found that positive valence in brand messages dominated all emotion-based tweets, whereas negative sentiments were comparatively few within each period. The pattern of these two sentiments remained unchanged irrespective of the years considered. Thus, we extracted positive and negative sentiments from the lexicon to analyse the variations in the residual emotions. To compare specific brand messaging concerning marketing activity during the pandemic, we selected the common themes found in the previous section.

These are the topics categorised under the marketing messages and digitalisation categories. In the timeframe from before to during the pandemic, “communication campaigns” and “online transactions” are the topics that belong to those categories, respectively, as shown in [Table 2];. In the timeframe encompassing the pandemic and its aftermath, we categorise “seasonal communication campaigns” as part of marketing messages, but “online transactions” and “mobile banking” were classified under digitalisation, as illustrated in [Table 3];. We compared the emotional patterns of issues in marketing messages for both the time periods under examination. Specifically, we analysed the emotional patterns of themes from before to during the pandemic by investigating “communication campaigns” and from during to after the pandemic by scrutinising “seasonal communication campaigns.” In the context of digitalisation, we could not compare the emotive patterns of “online transactions” from the period prior to the pandemic with those during it, as we discovered that the tweets categorised as “online transactions” (refer to [Table 2];) were

exclusively posted during the pandemic. Conversely, it was feasible to compare the emotional patterns of "online transactions" and "mobile banking" from the period during and after the pandemic, as the tweets categorised as either "online transactions" or "mobile banking" (refer to [Table 3];) were posted either during or after the pandemic.

Before visually comparing the comparative alteration in the emotions associated with the aforementioned topics, the Chi-squared Test of Homogeneity was applied using Pearson's Chi-squared test statistic for each pair of the times to ascertain whether the emotional changes were statistically significant across the years. To perform this analysis, the R programming language was used. The chi-square test is a nonparametric statistical test commonly used to examine associations or differences between the frequencies of categorical variables. There are three types of chi-squared tests. One is the Chi-squared Test of Homogeneity, the other one is the Chi-squared Test of Independence, and the last one is the Chi-squared Goodness of Fit Test. While their underlying assumptions are identical, their applications and the specific questions they address differ from each other. The chi-squared goodness of fit test tests whether an observed frequency distribution for a single categorical variable in one sample differs significantly from the expected frequency distribution. The "expected" distribution could be based on theory, prior knowledge, or a null hypothesis. On the other hand, the chi-square test of independence determines whether two variables are associated within a single sample. Finally, the Chi-Square Test of Homogeneity tests whether the distribution of one variable is identical across two or more independent groups. The comparison of these tests is given in [Table 4].

Table 4

Comparison of chi-square test statistics

Feature	Chi-squared Goodness-of-Fit Test	Chi-squared Test of Independence	Chi-squared Test of Homogeneity
Purpose	To determine if the observed frequency distribution of one categorical variable matches a hypothesised or expected distribution.	To determine if there is a statistically significant association (relationship) between two categorical variables from a single sample.	To determine if the distribution of a single categorical variable is the same (homogeneous) across two or more independent populations or groups.
Number of Samples Drawn	One sample	One sample	Two or more independent samples
Number of Categorical Variables Analysed	One	Two	One (its distribution is compared across groups)
Null Hypothesis (H ₀)	The observed frequencies match the expected (hypothesised) frequencies.	The two categorical variables are independent (not associated).	The distributions of the categorical variables were homogeneous (the same) across the populations/groups.

The chi-square test of homogeneity was identified as the appropriate test statistic for this research based on the provided explanation and specific reasons. The data first consists of three distinct independent groups, namely, tweets emerging from different time periods: prior to, during, and after the pandemic. The independence of observations is met because the data (tweets) from each period (prior, during, and after the pandemic) constitute distinct and independent groups. Therefore, a tweet posted in the prior period is independent of a tweet posted during or after the period. However, it is acknowledged that sometimes the same word in a tweet posted during the same period can refer to more than one emotion, but this issue,

which is handled with multi-labelling in machine learning, cannot violate the robustness of chi-squared tests. The second reason is that the Chi-squared Test of Homogeneity tests whether the distribution of emotion words (categorical variables) is homogeneous or different across these predefined time periods. In order to operationalise the test, the counts of the terms that refer to certain emotions were summed so that eight distinct values were gained for each of the two periods, as presented in [Table 5];. Having run a chi-square test of homogeneity analysis, the analysis proceeded with a visual representation of the relative changes in the emotions throughout the years in question.

Table 5

Data set used for the chi-squared test of homogeneity

Topic Category		The aggregate of terms of emotion		
		Emotion	Prior	During
Marketing Messages	Panel A	anger	122	2
		anticipation	732	24
		disgust	67	2
		fear	245	16
		joy	670	18
		sadness	137	6
		surprise	312	10
		trust	750	37
	Panel B	anger	35	225
		anticipation	142	938
		disgust	27	145
		fear	65	418
		joy	132	867
		sadness	63	253
		surprise	61	365
		trust	176	1073
Digitalisation	Panel C	anger	863	341
		anticipation	3397	1586
		disgust	459	167
		fear	1481	622
		joy	3198	1453
		sadness	883	333
		surprise	1493	685
		trust	3828	1787

We took certain steps to make the comparison possible. We initially employed the *stm* package's *findThoughts* function, which allows researchers to perform a thorough analysis on the identified topics. Essentially, topic models allocate each document (tweets in our case) to each topic (the topics under the column "Name of the topic" in [Table 2] and [Table 3];) with a distinct probability, indicating that each

topic contains all documents with a different probability (Blei & Lafferty, 2007). Consequently, we selected the documents (the tweets in our case) pertaining to each topic with posterior probability exceeding 0.20, as adjusted by the thresh argument of the *findThoughts* function, to enhance the representation of each discovered topic. Then, we calculated the overall sentiments of those tweets that referred to particular topics. Due to the significant variation in the quantity of tweets and their associated emotions across different periods, we standardised the emotions by computing the average weight of each emotion for each time frame, facilitating cross-comparisons over three years. Specifically, we divided the number of emotion-related words in a given period by the total number of emotion-related words in the same period. For instance, the average weight of anger was calculated as follows:

$$\text{Average weight of anger – related words} = \frac{\text{Total number of anger – related words}}{\text{Total number of all emotion – related words}} \quad (1)$$

Using the *ggplot2* package in R (Wickham et al., 2024), we finally visualised the outcomes in Figures 3 and 4 for the marketing messages and Figure 5 for digitalisation categories.

Marketing Messages

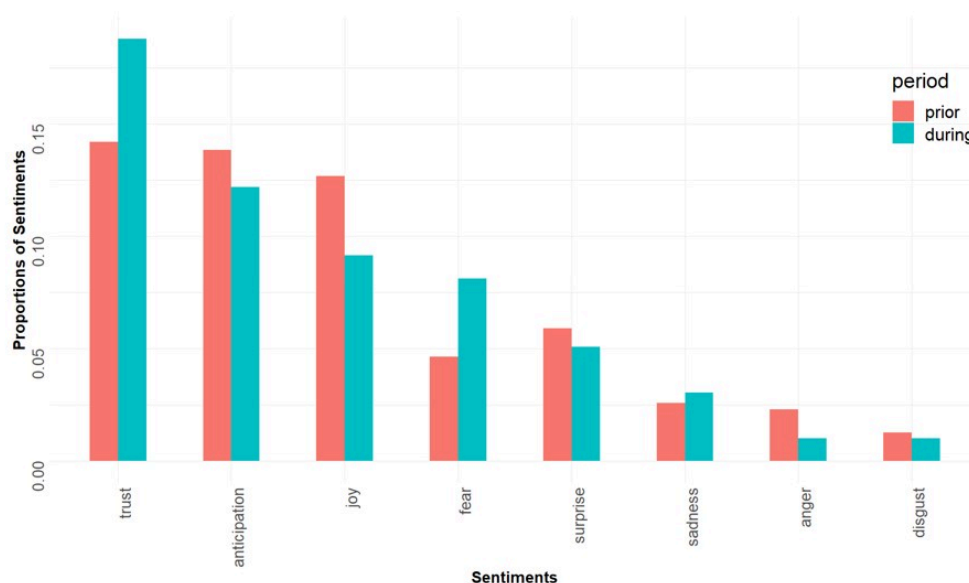
As anticipated, corporations have persisted in launching communication initiatives throughout the designated timeframe. However, when examining the campaigns over the course of these three years, discernible emotional patterns emerged. [Figure 3] demonstrates the significance of emotions in brand messages disseminated before and during the pandemic, whereas [Figure 4] indicates those shared during and after the outbreak. The comparative use of emotions fluctuated markedly across different periods, as depicted in the figures; nevertheless, these variations were not statistically significant, as evidenced by Pearson's chi-square test result. Specifically, as represented in Panel A of [Table 6], chi-squared test statistics indicated that there was no statistically significant difference in the emotional profile of marketing messages between the period prior to the pandemic and during the pandemic at the 0.05 significance level ($p = .1229$) (see [Table 5] Panel A for the data utilised). This implies that the distribution of emotions embedded in tweets that constitute topics belonging to the marketing message category was homogeneous across the two periods inspected. To calculate this value, a chi-square test was performed using Monte Carlo simulation and without continuity correction, as the data dimension is 8×2 . It is important to acknowledge that some of the expected cell frequencies in this comparison were less than 5, which may affect the reliability of the chi-squared approximation. However, the Monte Carlo simulation is capable of handling this violation. Likewise, the Pearson's chi-squared test statistic also points to a statistically nonsignificant difference in emotion patterns in marketing messages from the period during to the period after the pandemic under the 0.05 significant level ($p = 0.149$), as seen in Panel B of [Table 6] (see [Table 5] Panel B for the data utilised). This result indicates that while there were visual fluctuations in the figures, the overall pattern of emotions was not statistically different between these two periods. In other words, the distribution of emotions embedded in tweets that constitute topics belonging to the marketing messages category was also homogeneous across the two periods inspected (the during- and post-pandemic periods).

Table 6*Chi-squared Test of Homogeneity to compare emotions used in brands' social media messages*

Topic Category		Periods	χ^2	df^2	p -value
Marketing Messages	Panel A	Prior vs. During	11.58	NA	.1229
	Panel B	During s. Post	10.995	NA	.149
Digitalisation	Panel C	During s. Post	22.564	NA	.0019

Since the Monte Carlo simulation is not based on the chi-squared distribution, which is a theoretical distribution, the degree of freedom is not used in the calculation. The Monte Carlo simulation uses an empirical (simulated) distribution.

Figure 3 demonstrates that the analysis identified trust, anticipation, and joy as the predominant emotions, irrespective of the year under examination. Nonetheless, the relative prominence of some emotions fluctuated during the examined periods. Throughout the pandemic, we observed that brand communications emphasised terminology associated with trust. Likewise, phrases associated with fear were more common during the pandemic than before it. In contrast, during the pandemic, the use of terms associated with joy, anticipation, and surprise diminished. Although phrases associated with sadness, anger, and disgust were less frequently utilised than those pertaining to other emotions, we noted a marginal increase in the prominence of sadness in brand communications, whereas terms connected to anger and disgust diminished.

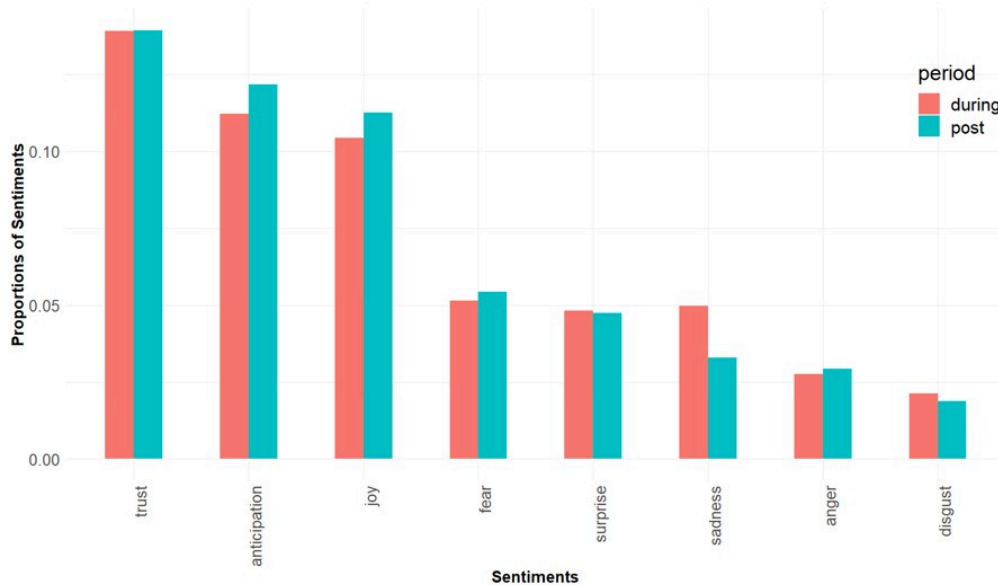
Figure 3*Sentiments in marketing messages before and during COVID-19*

Upon analysing the two years that included the pandemic and its aftermath, we identified a comparable pattern regarding the prevailing emotions observed in the preceding period. [Figure 4] illustrates that the predominant emotions employed by the brands in their communications during both periods were joy, anticipation, and trust. The anticipation and joy incrementally heightened from one year to the next. Correspondingly, the relative prominence of fear-related words escalated post-pandemic, suggesting that the repercussions of the global pandemic were also reflected in the brand's communications in the subse-

²Since the Monte Carlo simulation is not based on the chi-squared distribution, which is a theoretical distribution, the degree of freedom is not used in the calculation. The Monte Carlo simulation uses an empirical (simulated) distribution.

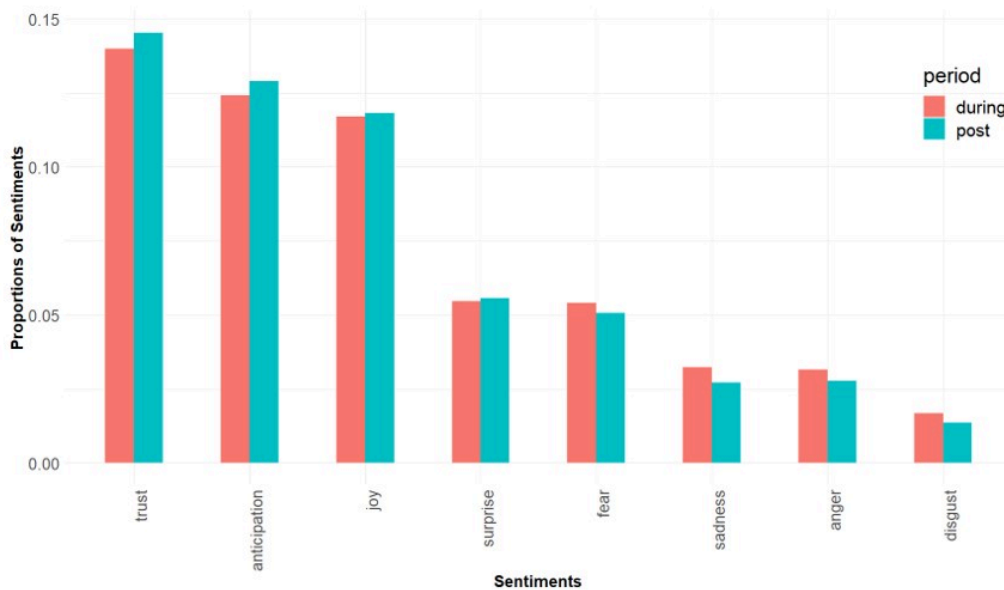
quent year. From the pandemic period to the post-pandemic phase, there was a significant reduction in the prevalence of phrases related to sadness. Despite the absence of variation in the relative significance of trust-related phrases over different times, it consistently remained the predominant feeling in both intervals, as noted in previously analysed timeframes.

Figure 4
Emotions in marketing messages during and after the pandemic



Digitalisation

As presented in [Table 3], we gathered “online transactions” and “mobile banking” under the “digitalisation” category. Then, we consolidated the tweets pertaining to these two subjects, following which the chi-squared test and sentiment analysis were employed to examine the progression of emotion-based patterns in messages concerning digitalisation during and post-pandemic, utilising the data presented in [Table 5] Panel C. The Pearson’s chi-square test statistic determined that the relative changes in emotions seen between the time periods, as depicted in [Figure 5], were statistically significant. Specifically, as represented in [Table 6] Panel C, the chi-squared test indicated a significant difference in emotion patterns in digitalisation from the period during to the period post-pandemic at the 0.005 significant level ($p = 0.0019$). This indicates that the distribution of emotions is not uniform across the two periods analysed for tweets categorised under digitalisation from during to post-pandemic. Figure 5 offers preliminary evidence that trust, anticipation, and joy consistently constituted the principal emotions integrated by the companies into their X messages, irrespective of contextual variations. In the post-pandemic period, positive emotions have gained prominence in brand messaging. This improvement can be ascribed to the decreased relative use of fear-, sadness-, anger-, and disgust-related terms, in contrast with the increased relative usage of those related to trust, anticipation, joy, and surprise.

Figure 5*Emotions in digitalisation-related messages during and after the pandemic*

Wording Pattern

Upon initial examination of the trust-related vocabulary, we noted that brands incorporated health and protection-related concepts, such as insurance, protection, and assurance, into their communication campaign messages amidst the pandemic. Furthermore, the word "trustworthy" is also among the most frequently repeated terms. Additionally, we observe that "continuity" and "practicality" remain the most favoured terms throughout this period. Moreover, money categorised under trust is frequently employed in discourse during the pandemic. After the pandemic, however, this pattern has no longer remained apparent, as all terms but "health" and "insurance" have ceased to be among the most frequently occurring words. Likewise, certain terms like "winning", "effective", "engaging", "comfort", and "flawless" have lost their priority after the global pandemic, although they were preferred prior to the pandemic among the most frequent words. In contrast, even after the global pandemic, the brands incorporated terms such as "wonderful", "unique", "pleasant", "natural", and "strong", which had been in use prior to the crisis. Figure 6 presents all these wording variations on the left side with red-coloured bar graphs.

Marketing Messages

Upon initial examination of the trust-related vocabulary, we noted that brands incorporated health and protection-related concepts, such as insurance, protection, and assurance, into their communication campaign messages amidst the pandemic. Furthermore, trustworthy directly is also placed among the mostly repeated words. Additionally, it is observed that the terms "continuity" and "practicality" are the most favoured ones throughout this period. Moreover, money categorised under *trust* is frequently employed in discourse during the pandemic. After the pandemic, however, this pattern has no longer remained apparent, as all terms except health and insurance have ceased to be among the most frequently occurring words. Likewise, certain terms like winning, effective, engaging, comfort, and flawless lost their priority after the global pandemic, although they were preferred prior to the pandemic among the most frequent words. In contrast, even after the global pandemic, the brands incorporated terms such as wonderful, unique,

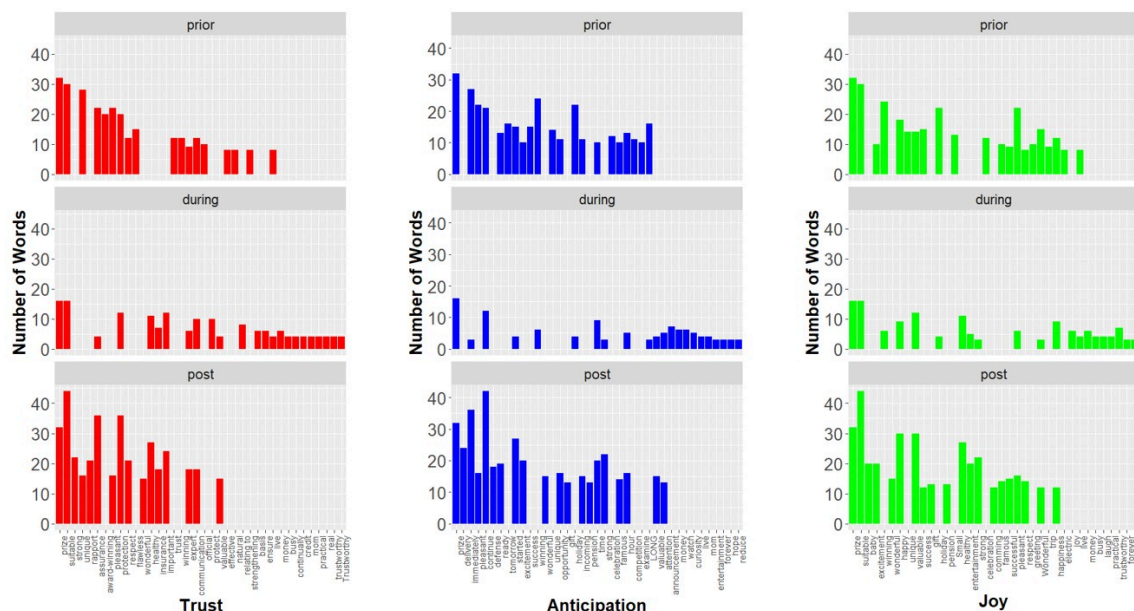
pleasant, natural, and strong, which had been in use before the crisis. All these wording variations are presented on the left side of [Figure 6] with red-coloured bar graphs.

With the scope of *anticipation* in marketing messages, certain terms such as "competition", "success", "unique", and "celebration" that were prevalent prior to the pandemic have no longer been frequently used during the pandemic. Similarly, pleasant, excitement, opportunity, and famous were ranked among the frequent words before the pandemic and also vanished during the period but reappeared after the pandemic again. In contrast to the period before the pandemic, valuable, attention, money, curiosity, live, entertainment, hope, and forever became the frequently preferred terms during the pandemic. Except for the valuable and attentive ones, others have not been observed again after the pandemic. The wording variations associated with anticipation are visually depicted in the middle of [Figure 6] with blue-coloured bar graphs.

Before the pandemic, the terms that were predominantly employed by brands and classified under the emotion of joy were as follows: unique, celebration, greeting, and trip. These terms, however, have appeared neither during nor after the pandemic. On the contrary, other terms belonging to the same category, such as "excitement," "successful," and "famous," have maintained prominence in both the pre- and post-pandemic periods, despite not ranking among the most frequently occurring words throughout the pandemic. Other words that have been identified as associated with trust are money, busy, practical, trustworthy, health, and hope. Health remains one of the most frequently occurring terms among these, even in the aftermath of the pandemic. In addition, the terms "strong" and "entertainment" are frequently employed in both the period preceding and following the pandemic. Last but not least, "wonderful" has become a frequently used word after the pandemic, although it was not so frequently used before and during the pandemic. Finally, the right panel of [Figure 6] illustrates the changes in wording patterns related to the emotion of joy.

Figure 6

Changes in the use of terms related to marketing messages over the years in question



Digitalisation

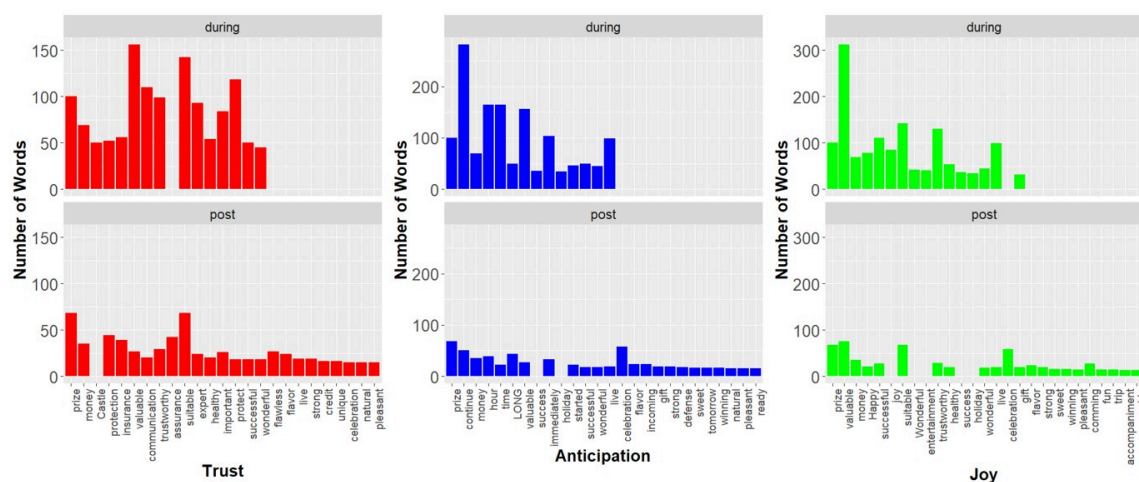
As explained in previous sections, we were unable to compare the emotional patterns of “online transactions” from the first timeframe under consideration (see [Table 2];) and categorised under the digitalisation category across the two years because the tweets were posted not before but rather only during the pandemic. On the other hand, the tweets we labelled as “online transactions” and “mobile banking” (see [Table 3];) were posted during or after the pandemic. Therefore, we could compare the emotional patterns of these topics across the timeframes from during to after the pandemic. Consequently, [Figure 7] consists of the terms that belonged to “online transactions” and “mobile banking.” The visual representation illustrates the changes in vocabulary usage of three emotions (i.e., trust, anticipation, and joy) within the domain of digitalisation.

In terms of *trust*, we have observed that health-related terms, including “healthy,” “insurance,” and “protect,” are among the most frequently used words in both time periods with regard to trust. “Trustworthy,” “valuable,” “successful,” and “expert” are the other terms referring to the trust and are used mostly not only during but also after the pandemic. Communication has become prominent during the pandemic in brand messages categorised under digitalisation, and this term has maintained its significance even after the pandemic. “Money” is also another term used frequently in digitalisation pertaining to brand messages in both periods. Aside from these, particular terms have gained prominence after the pandemic, including “assurance,” “flawless,” “live,” “strong,” “unique,” “natural,” “celebration,” and “pleasant,” although they were not used often during the pandemic. The left panel of [Figure 7] with red-coloured bars shows the changes in wording patterns associated with the emotion of trust.

Similar to the terms used for referring to trust and anticipation in terms of digitalisation, money, valuable, successful, trustworthy, wonderful, and healthy are also the prominent words used to refer to the emotion of joy. In addition, the terms “happy” and “live” are frequently associated with joy. Nevertheless, although “joy” and “entertainment” are frequently used terms to denote joy during the pandemic, they are not placed within the most frequent words after the pandemic. Instead, celebration, strong, pleasant, fun, and trip have gained prominence in the aftermath of the pandemic. Finally, the right part of the bar graphs in [Figure 7] visually depicts the changes in wording patterns belonging to joy.

Figure 7

Changes in the use of terms related to digitalisation during and after COVID-19



Discussion

In this study, the initial step involved conducting a series of text mining analyses on the most frequently discussed topics in the social media communications (i.e., on X) of specific brands spanning a period of three years, including periods preceding, during, and following the pandemic. After identifying the overarching topics, we proceeded to choose particular ones that are fundamentally associated with business operations: digitalisation and marketing messages. Next, we examined the emotion patterns of these topics in greater detail, focusing on trust, anticipation, and happiness. The final stage involved the identification of the specific terms responsible for eliciting these emotions in brand tweets.

The results of the study signify a nonsignificant difference in emotional patterns when comparing brand messages within the marketing category across the specified years; however, a significant difference was observed in the topics regarding digitalisation when contrasted with the years during the pandemic and its aftermath. This result indicates that corporations have altered their communication strategies regarding digitalisation messages in response to pandemic-related necessities while maintaining relative consistency in their marketing messages. In alignment with our findings, research in the consumer electronics industry reveals that corporations primarily utilise the emotional themes of joy, anticipation, and trust in their social media messaging during times of disruptive events. Moreover, a positive attitude constantly prevails across all channels (Pezoa-Fuentes et al., 2023). Consistent with recent research (Dhar & Bose, 2022), our analysis confirms that brands in Türkiye emphasise continuity during the pandemic, openly communicating this notion through their business-focused social media content. Furthermore, we have demonstrated in these posts that during crises, businesses seek to involve the community and convey hope (Arora et al., 2022). Similar to the emergence of trust as a key factor influencing human behaviour during the pandemic (Arora et al., 2022), we also see this dominant emotional pattern in the brand messages under examination. Research by Mathayomchan et al. (2023) indicates that when the impact of the pandemic diminishes, public discourses exhibit increased optimism, leading to a substitution of negative narratives with positive ones. Our study's analysis of brand messages shows similar patterns.

The notions of fear and trust mostly shaped the public discourse throughout the pandemic. Our research similarly indicates that brands use specific wording, particularly regarding trust during the pandemic, and the use of fear-related phrases significantly increases in the same period. Li and McCrary (2022) indicate that customers experience anticipation as one of the most favourable feelings throughout the pandemic, whereas they regard surprise less positively. Our findings reveal that the brand communications in our study align with these results, as the relative utilisation of surprise diminished during the pandemic, whereas anticipation emerged as one of the most significant emotions present in brand messaging. In addition to common business-related communications, in accordance with previous research (Farmaki et al., 2022), the companies featured in our study specifically demonstrate their solidarity with people impacted by the pandemic and natural catastrophes. Moreover, employee well-being is frequently articulated in brand messages, which aligns with the findings from earlier studies (Scheiwiller & Zizka, 2021).

The scarcity of extensive research on brand content in social media necessitates that marketing professionals seek help for creating appropriate social media content (Pezzuti et al., 2021). Furthermore, this demand becomes very imperative during emergencies. As Srinivasan et al. (2022) emphasises, research focused on company-generated material on social media can contribute to an expanding body of literature. Our research aims to address this need by employing automated text mining tools on a considerably large dataset of domestic and multinational brands operating in Turkey, taking the pandemic as a reference crisis.

The literature remains deficient in comparative studies that encompass the pre-, during-, and post-pandemic periods, despite the existence of particular studies focusing solely on the pandemic period (Hesse et al., 2021; Mangiò et al., 2021; Farmaki et al., 2022). Our research also addresses this gap by applying its methods to three unique historical periods.

Limitations and Future Research

We exclusively conducted our analysis using Turkish texts. Although we have tried to be as sensitive as possible to control likely issues—for instance, by employing manually coded regex patterns—that might have arisen during the analysis, the outcomes may inherently encompass misidentifications because the algorithms utilised in this study (e.g., Structural Topic Modelling (STM)) are more applicable to English texts. Due to this inability of the software, we were unable to run a robust lemmatisation process to eliminate the words that have the same lemmas. This issue might have resulted in dirty data. Therefore, future research can follow a more robust procedure to increase the purity and representativeness of the data. Moreover, we tried to eliminate certain bulks of letters that remained after the data cleaning process and seemed like meaningful words but actually had no meaning by using regex patterns. This process may have resulted in a partial loss of information in the dataset. Further research can adopt a different approach to eliminate such words without the risk of losing information. We designed our research from an exploratory perspective. Potential investigations may assess the efficacy of crisis communication by analysing responses to particular social media posts, given that our dataset comprises specific social media metrics, including number of followers, likes, retweets, and tweet dates. Researchers can conduct industry-level analyses by realising specific arrangements in our dataset to execute a comparative examination of outcomes both within and outside the industries. While we used X as our primary data source, other research can apply a similar analysis procedure on other social media platforms such as LinkedIn or Facebook. Our study is centred on two prevalent business-related topics (e.g., communication campaigns and digitalisation) during the specified time periods (from 2019 to 2022), and we have examined three emotions (i.e., trust, anticipation, and joy) and the corresponding expressions for these topics. Additionally, future research may investigate the communication patterns and probable changes of other topics over the next three years. Instead of differentiating the domestic brands from the international ones, we have analysed them all together. However, comparing the social media discourses of local brands with the discourses of international ones might be fruitful research for future studies. In our study, we treated the pandemic as a reference crisis. However, since it is argued that the future is subject to prospective crises (Hesse et al., 2021), the appropriate communication will preserve its importance for the organisations even during any other crisis timeframe. From this perspective, marketing practitioners may employ the text mining methodology that we followed in our analysis to enhance their marketing communications during potential crises. Finally, researchers could also investigate why the emotional tone of marketing-centred messages does not differ significantly across different periods of the crisis.



Peer Review	Externally peer-reviewed.
Author Contributions	Conception/Design of Study- M.M.C., E.K.; Data Acquisition- M.M.C.; Data Analysis/ Interpretation- M.M.C., E.K.; Drafting Manuscript- M.M.C.; Critical Revision of Manuscript- E.K.; Final Approval and Accountability- M.M.C., E.K.
Conflict of Interest	The authors have no conflict of interest to declare.
Grant Support	The authors declared that this study has received no financial support.

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