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Emojis analysis at international trade shows in five countries: ex- and post-COVID-19

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Abstract

Purpose – The purpose of this paper is, first, to predict eWOM volume based on emoji presence in a tweet, amount of emojis in a tweet and time frame (posting date ex ante COVID-19 or posting date ex post COVID-19) influences. And second, to identify whether there are differences between the samples and a moderation effect of country on the relationship studied. All in a B2B context, particularly in international trade shows (ITSs).

Design/methodology/approach – The data was collected from X (formerly and still commonly known as Twitter), from 10 ITSs in five countries (France, Spain, the UK, Mexico and the USA), considering two ITSs per country. In total, 9,329 tweets were analyzed and content analysis was used: 3,566 tweets from Period 1, posting date ex ante COVID-19 and 5,763 tweets from Period 2, posting date ex post COVID-19.

Findings – The results show, first, in a B2B context, that tweets with emoji presence, more emojis and tweets posted before the pandemic have the highest volume of eWOM. Second, that culture moderates the volume of eWOM. Specifically, in the US sample, all predictors significantly drive eWOM volume, even though the USA is the country that uses the least amount of emojis on Twitter.

Originality/value – This research answers a gap in the literature, contributing to empirical research on the adoption, use, measurement and effect of emoji usage in real-world communication in different countries.

Keywords eWOM, Emoji, Time frame: countries, B2B, COVID-19, Social media, Twitter (X)

Paper type Research paper

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Análisis DE emojis EN ferias internacionales DE comercio EN cinco países: antes Y después DE covid-19

Resumen

Objetivo – Este artículo intenta, en primer lugar, predecir el volumen de eWOM basado en (1) la presencia de emojis en un tweet, (2) la cantidad de emojis en un tweet y (3) los efectos del marco temporal (fecha de publicación antes de COVID-19 o fecha de publicación después de COVID-19). En segundo lugar, identifica (4) si existen diferencias entre las muestras y un efecto de moderación del país sobre la relación estudiada. Todo en un contexto B2B, particularmente en Ferias Internacionales de Comercio (ITS).

Diseño/metodología/enfoque – Los datos fueron recopilados de X (anteriormente y aún comúnmente conocido como Twitter), de 10 Ferias Internacionales de Comercio (ITS) en 5 países (Francia, España, el Reino Unido, México y Estados Unidos), considerando 2 ITS por país. En total, se analizaron 9,329 tweets, y se utilizó el análisis de contenido: 3,566 tweets del periodo 1, fecha de publicación antes de COVID-19, y 5,763 tweets del periodo 2, fecha de publicación después de COVID-19.

Resultados – Nuestros resultados muestran, en primer lugar, en un contexto B2B, que los tweets con (i) presencia de emojis, (ii) más emojis y (iii) tweets publicados antes de la pandemia tienen el mayor volumen de eWOM. En segundo lugar, que la cultura modera el volumen de eWOM. Específicamente, en la muestra de Estados Unidos, todos los predictores influyen significativamente en el volumen de eWOM, aunque Estados Unidos es el país que usa la menor cantidad de emojis en Twitter.

Originalidad/valor y Originalidad/valor – La presente investigación responde a una brecha en la literatura, contribuyendo a la investigación empírica sobre la adopción, uso, medición y efecto del uso de emojis en la comunicación en el mundo real en diferentes países.

Palabras clave eWOM, emoji, marco temporal, países, B2B, COVID-19, redes sociales, Twitter (X)
Tipo de artículo Trabajo de investigación

国际贸易展会中表情符号的分析：基于五国数据的covid-19前后对比研究

摘要

研究目的 – 本研究的首要目标是预测电子口碑（eWOM）传播量, 并探讨以下因素的影响：(1) 推文中是否包含表情符号; (2) 推文中表情符号的数量; (3) 发表时间, 即COVID-19前（Ex-Ante COVID-19）或COVID-19后（Ex-Post COVID-19）。其次, 本研究旨在识别(4) 样本之间是否存在差异, 以及国家因素是否对所研究关系产生调节效应。本研究聚焦于企业间（B2B）交流场景, 尤其是在国际贸易展会（International Trade Shows, ITSs）背景下展开分析。

研究设计 – 本研究数据来源于社交媒体X（原Twitter）, 涵盖来自五个国家（法国、西班牙、英国、墨西哥和美国）共计10场国际贸易展会, 每个国家选取2场展会进行分析。最终, 共计收集并分析了9,329条推文, 其中3,566条推文来自COVID-19前（Ex-Ante COVID-19）, 5,763条推文来自COVID-19后（Ex-Post COVID-19）。研究采用内容分析方法对数据进行处理。

研究发现 – 首先, 在B2B语境下, 研究结果表明：(i) 包含表情符号的推文, (ii) 具有更多表情符号的推文, 以及(iii) 发布于COVID-19前的推文, 均表现出更高的电子口碑传播量（eWOM volume）。其次, 文化因素在电子口碑传播量上具有调节作用。具体而言, 在美国样本中, 所有预测变量均显著影响电子口碑传播量, 尽管美国是五国中在Twitter平台上使用表情符号最少的国家。

研究原创性与价值 – 本研究填补了现有文献的研究空白, 为不同国家真实社交媒体交流中表情符号的采用、使用模式、测量方法及其传播效果等方面提供了贡献。

关键词 电子口碑（eWOM）, 表情符号, 时间框架, 国家, B2b covid-19 社交媒体, Twitter（X）
文章类型 研究型论文

1. Introduction

This research examines the role of emojis in B2B digital marketing across countries. Emojis enhance message clarity and engagement in online interactions (Luangrath *et al.*, 2022; Ge and Gretzel, 2018). In formal B2B communication, understanding their impact on eWOM volume (e.g. retweets on Twitter) is key, especially post-COVID when digital engagement grew. By exploring cross-cultural differences in emoji interpretation, this study addresses how emojis affect brand perception and purchasing intentions globally.

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In this scenario, the aims of our study are both to predict eWOM volume based on emoji presence, amount of emojis and time frame (posting date ex ante COVID-19 or posting date ex post COVID-19) in five countries and to identify differences between the samples and a moderation effect of the country on the relationship studied.

This study will contribute to marketing literature in B2B contexts differently. First, marketing literature has recognized social media's utility in promoting international trade shows (ITSs) (Lapoule and Rowell, 2016), improving their performance (Singh *et al.*, 2017).

Second, this paper focuses on the uses of emojis, which are less analyzed than other social media tools in B2B contexts (Balaji *et al.*, 2023). In this sense, despite B2B firms' expanding use of social media, they still face significant challenges in creating compelling messages that effectively engage customers (Balaji *et al.*, 2023).

Third, the study adds value by identifying whether there are differences among samples in emoji presence, amount of emojis, time frame, eWOM volume and whether there is a moderation effect of the country on the relationship studied. Given that the eWOM studies have been focused on a single country (Donthu *et al.*, 2021), our study amplifies knowledge about this variable.

At the general level, this study responds to the recent call for research on social media (Dwivedi *et al.*, 2021). In addition, the measurement of the eWOM volume by companies is another recent research call (Dwivedi *et al.*, 2021). Moreover, researchers have called for studies about emoji usage in both the real-world communication field (Bai *et al.*, 2019) and among different contexts (McShane *et al.*, 2021). In addition, there is also a recent call for research about the differences between countries in the use of social media (Dwivedi *et al.*, 2021).

In this sense, this paper studies these differences in a particular B2B context as there is a lack of studies on this topic (Bai *et al.*, 2019). Then, our findings will enhance our understanding of cross-cultural differences in the usage of emojis among countries with three different languages (English, Spanish and French).

To reach the objectives, the data was collected from X (formerly and still commonly known as Twitter), from 10 ITSs in France, Spain, the UK, Mexico and the USA (considering two ITSs per country). The tweet was used as the unit of analysis. In total 9,329 tweets were analyzed: 3,566 tweets ex ante COVID-19 and 5,763 tweets ex post COVID-19.

2. Theoretical review

2.1 eWOM

After a literature review from 1996 to 2019, Babić Rosario *et al.* (2020) define eWOM as consumer-generated, consumption-related communication using digital tools, primarily aimed at other consumers. Suggest that Social Capital Theory helps investigate eWOM formation and spread, particularly how online social network features influence eWOM. This theory emphasizes that connections within social groups generate relational resources, shaped by the valence (nature and quality) and volume (quantity) of shared content. eWOM thrives on social networks like Twitter, where users connect with people or organizations they do not know, spreading new information (Phua *et al.*, 2017). Creating and sharing relevant brand content builds strong brand relationships (Hollebeek and Macky, 2019). Twitter, widely used by firms (Sridevi *et al.*, 2020), is powerful for fast information dissemination (Barhorst *et al.*, 2020) and promoting eWOM through retweets, which share content within users' networks (Kim *et al.*, 2014; Rivadeneira *et al.*, 2021).

Grounded in Social Capital Theory, our study examines eWOM within the context of Twitter, defining eWOM volume as the number of retweets (Kim *et al.*, 2014; Soboleva *et al.*, 2017). Retweets are considered "another form of engagement" (McShane *et al.*, 2021), making them a relevant metric for this analysis. This variable was selected as a dependent variable to be explained, given that it is an outcome of the online communication process in social media contexts such as Twitter (Son *et al.*, 2019); the effect of the eWOM volume has a stronger

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impact on sales than eWOM valence (Babić Rosario *et al.*, 2020) and researchers have called for studies about emoji usage in the real-world communication context (Bai *et al.*, 2019) in different contexts (McShane *et al.*, 2021).

2.2 Emojis

In network communication, the emoji is used frequently (Bai *et al.*, 2019), is part of digital content marketing (Holliman and Rowley, 2014) and represents a new form of interaction. Not in vain, in the academic field, the research about emojis is growing and is related to areas of communication and marketing, among others (Bai *et al.*, 2019). Using emojis as a language transcends borders, being the fastest-growing language globally (Kerslake and Wegerif, 2017). Specifically, emojis increase customer engagement as a visual stimulus, complementing or replacing the written language (Valenzuela-Gálvez *et al.*, 2022).

Many contents can be expressed using emojis (Bai *et al.*, 2019). Specifically, eight categories are included in the emoji reference website: 😀 Smileys and People, 🐻 Animals and Nature, 🍔 Food and Drink, ⚽ Activity, 🚀 Travel and Places, 💡 Objects, 💕 Symbols and 🎌 Flags (https://emojipedia.org/).

Furthermore, emojis have been used to analyze emotional associations with food and beverages (Jaeger *et al.*, 2017).

Emojis have been analyzed following diverse theories. McShane *et al.* (2021) apply the elaboration likelihood model (ELM), suggesting that emojis act as peripheral cues that enhance message impact without requiring deep cognitive processing. Mladenović *et al.* (2023) combine the Dual Process Theory and emotional contagion to examine whether exposure to emojis increases purchase intention and campaign effectiveness. Almaguer *et al.* (2024) integrate Sign Theory with linguistics to position emojis as a significant evolution in modern language. This paper follows the ELM (Petty and Cacioppo, 1986), as used in previous studies (McShane *et al.*, 2021; Luangrath *et al.*, 2022).

Acknowledging social media's role in promoting ITSs (Lapoule and Rowell, 2016) and the use of emojis in digital marketing (Holliman and Rowley, 2014), we predict emoji usage significantly influences eWOM volume in B2B contexts like ITS. Three key drivers of eWOM volume have been identified:

- emoji presence (McShane *et al.*, 2021);
- emoji quantity (McShane *et al.*, 2021); and
- time frame (pre- or post-COVID-19) (Das, 2021; Liu *et al.*, 2022).

Based on this, we defend that emojis impact eWOM volume, influenced by these factors.

2.2.1 Emoji presence. More and more brands use emojis (Cavalheiro *et al.*, 2022) because, at a general level, their presence in promotional communications increases purchase intentions, at least for hedonic products (Das *et al.*, 2019). Even more, emojis are positively related to brand engagement (McShane *et al.*, 2021). Specifically, McShane *et al.* (2021) found that emojis in a tweet increase the eWOM volume. In addition, Cavalheiro *et al.* (2022) noted a greater acceptance of brands that use emojis when advertising on social media. Moreover, Liu and Jansen (2018b) proved that emojis can increase responses. In the food arena, Indwar and Mishra (2022) found a significant effect of emoji presence on eWOM, confirming the effectiveness of emoji presence in communication in the digital age without face-to-face communication. In the same line, Luangrath *et al.* (2022) demonstrated that the emojis' presence acts as a visual stimulus that enhances information processing, which increases the probability of a message being shared in a B2B context (eWOM volume). Also, on Facebook, some authors found that emojis positively influence content sharing (Osorio Andrade *et al.*, 2020).

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In sum, based on the previous literature, we propose the following hypothesis:

H1a. Emoji presence positively influences the electronic word-of-mouth volume in an international business-to-business context.

2.2.2 Amount of emojis. Literature has proved that emoji quantity positively influences eWOM volume on Twitter (McShane *et al.*, 2021). In other words, the more emojis a tweet has, the more retweets it will have (McShane *et al.*, 2021).

In this sense, Pınarbaşı and Kırçova (2021) found that tweets in the Turkish food and beverage industry contained an average of 1.94 emojis. Pereira and D'Urso (2021) suggest that more emojis enhance message persuasiveness by making it more relatable and engaging. Similarly, Luangrath *et al.* (2022) showed that a higher emoji counts boosts emotional impact and engagement. Previous research also indicates that a larger number of emojis increases message attention.

In sum, the influence of emoji usage on the eWOM volume on Twitter can be analyzed through the amount of emojis (McShane *et al.*, 2021). So, based on the previous literature, we propose the following hypothesis:

H1b. The amount of emojis positively electronic word-of-mouth volume in an international business-to-business context.

2.2.3 Time frame. In the B2B context, the pandemic has posed challenges for firms, particularly in communication during crises (Crowe, 2012). Accurate information dissemination has become crucial, given the increasing influence of social media (Sharma *et al.*, 2020). Although COVID-19 has driven eWOM (Dang and Raska, 2021), emojis and eWOM were already significant before the pandemic. Thus, the third objective examines the time frame, defined by the tweet's publication date (Villamediana *et al.*, 2019). Specifically, we compare tweets posted ex ante COVID-19 and ex post COVID-19, as Das (2021) demonstrated that emoji usage per tweet changed before and after the pandemic. Liu *et al.* (2022) also found a reduction in emoji use ex post COVID-19 in China and Ye and Ho (2023) noted that the COVID-19 time frame affects how messages are received and shared, impacting eWOM.

Based on literature and the justification of the pandemic situation, we propose the following hypothesis:

H1c. The time frame (ex ante COVID-19 versus ex post COVID-19) influences the electronic word-of-mouth volume in an international business-to-business context.

2.3 Differences between countries

Cultural differences in Twitter users can be seen in emoji frequency (Li *et al.*, 2019), and in the business field, culture affects how companies use social networks (Cummings and O'Neill, 2021; Dwivedi *et al.*, 2021). eWOM and emoji usage vary across cultures (Dang and Raska, 2021), with studies showing that emoji use depends on culture and country (Krejtz and Borkowski, 2020; Cummings and O'Neill, 2021; Levi *et al.*, 2024). Kejriwal *et al.* (2021) suggest some languages and countries use emojis more. Krejtz and Borkowski (2020) explore cultural influences on emoji usage, whereas Wang and Wang (2022) show how cultural context affects the relationship between emojis and eWOM volume.

In sum, the literature has analyzed the data in two ways: a global analysis of emoji usage and emoji usage by country (Das, 2021). Given this, this study will try to answer the research gap identified by experts, related to differences between countries in their use of social media (Dwivedi *et al.*, 2021; Wang and Wang, 2022). We expect that differences exist between the countries in emoji presence, amount of emojis, time frame and eWOM volume. We also

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suppose that the country moderates the relationship between predictors and responses in our study. In this sense, our second and third hypotheses are the following:

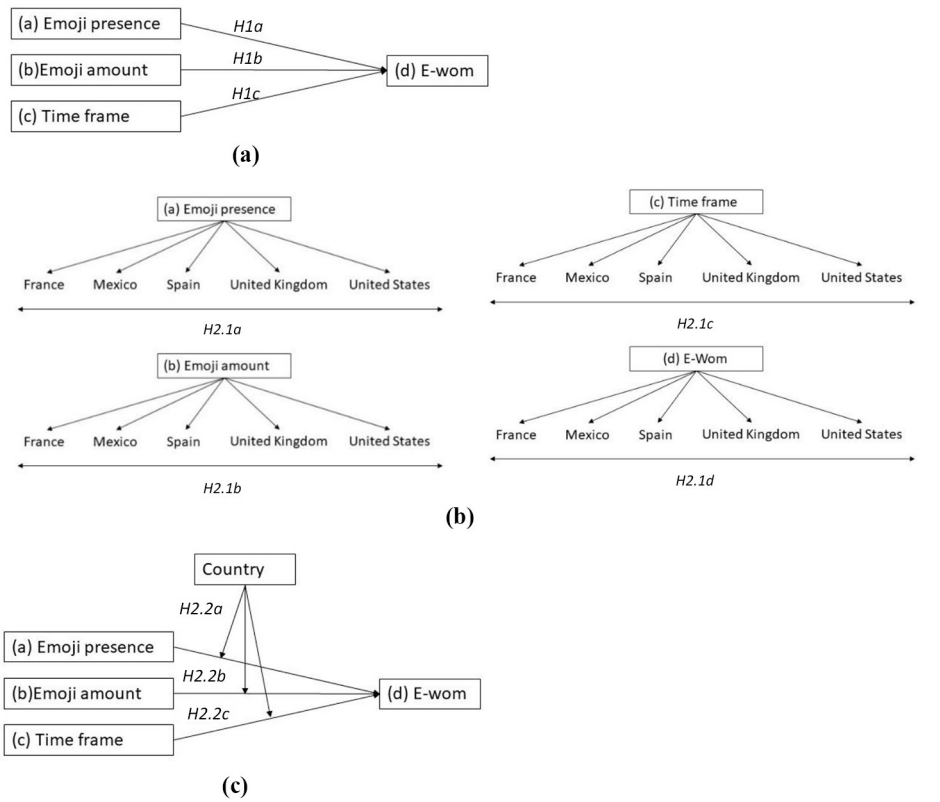
H2.1. There are differences between countries in emoji presence, amount of emojis, time frame and electronic word-of-mouth volume in an international business-to-business context.

H2.2. There are differences between countries in the relationship between emoji presence, amount of emojis, time frame and electronic word-of-mouth volume in an international business-to-business context.

Figure 1 represents all specific hypotheses in our study.

3. Method

The data was collected from Twitter, using a tweet as the unit of analysis (Sridevi *et al.*, 2020). Twitter is an appropriate platform for research because it is public, it is possible to



Note(s): (a) *H1*) Influences on E-wom; (b) *H2.1*) differences between countries in each variable; (c) *H2.2*) moderation of country in the relationship studied

Figure 1. Proposed hypotheses

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investigate each tweet, the tweets can be taken simultaneously and it provides enough data for thorough analysis (Leek *et al.*, 2019). ITSs were identified on Twitter through their handles beginning with the @ sign. All tweets and the retweet count for each tweet were collected from Twitter.

COVID-19 was declared a pandemic on March 11, 2020, by the World Health Organization (Chakraborty *et al.*, 2020). The tweets were collected from June 21, 2019, to January 31, 2022, using the Twitonomy subscription service (Soboleva *et al.*, 2017) offered by the website www.twitonomy.com. The periods analyzed were two, first, Period 1 from June 21, 2019, to March 10, 2020 (posting date ex ante COVID-19). Period 2 from March 11, 2020, to January 31, 2022 (posting date ex post COVID-19). Period 2 is 2.6 times that of Period 1 because the pandemic impacted the global service markets (Kabadayi *et al.*, 2020).

Due to the characteristics of the data, we used non-parametric techniques to test the hypotheses, including contingency tables (chi-squared), the Kruskal–Wallis test and regression analyses (optimal scaling). For *H1a–H1c*, we used regression analyses with optimal scaling using the CATREG algorithm (Gifi, 1990), which quantifies categorical variables and optimizes regression coefficients for categorical data (Kooij, 2007). This method has been effectively applied in marketing studies (Villamediana *et al.*, 2019) and offers advantages like not requiring residual normality, linear relationships or normal data distribution (Hartmann *et al.*, 2009). For *H2*, to examine the relationship between emoji presence, quantity, time frame and eWOM in each sample and to analyze country-specific differences and moderation effects, we conducted multiple regression analyses with optimal scaling, following prior research (Wang and Chung, 2020; Hayes and Rockwood, 2017).

3.1 Food and beverage international trade shows selection

The food and beverage ITSs were collected from the website, www.feriasalimentarias.com, allowing free and up-to-date information on international food fairs. The ITSs were published on March 13, 2022, on the www.feriasalimentarias.com website. Convenience or directed sampling was used to select the ITSs from the www.feriasalimentarias.com website (Geldres-Weiss *et al.*, 2021). In sum, the final sample included 9,329 tweets, from 10 ITSs in five countries (France, Spain, Mexico, the UK and the USA), considering the following criteria: ITSs with Twitter accounts; ITSs with a minimum of 300 new tweets; non-annual ITS were excluded; countries with less than two ITS were excluded; and it was selected the two ITSs with more emojis per country.

3.2 Emoji presence and amount of emojis

Following McShane *et al.* (2021), tweets were coded by emoji presence and the amount of emojis. To code the emoji presence, we adopted Unicode Full Emoji Data v3.0 as our list for coding emoji.

As shown in Table 1, we analyzed 9,329 tweets from 10 ITSs across five countries. We identified whether the tweets used emojis and the number of emojis used. Specifically, we found 370 emojis in the French sample, 1,060 in the Mexican sample, 527 in the Spanish sample, 740 in the British sample and 2,916 in the American sample.

We have also classified tweets into two categories according to their publication date (time frame): before the pandemic (ex ante COVID-19) and after the pandemic (ex post COVID-19).

4. Analysis and discussion

Data was analyzed using SPSS, v.27. A statistical significance level of p-value < 0.05 (α) and a 95% confidence interval were considered to accept or reject the hypotheses.

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Table 1. Descriptive statistical for predictors and response variable

		Frequency					
Categorical variables							
	Dimension	France	Mexico	Spain	UK	USA	All countries
Emoji presence	No	370	1,060	527	740	2,916	5,613
	Yes	888	794	829	453	752	3,716
Time frame	Ex ante C.	833	354	538	439	1,402	3,566
	Ex post C.	425	1,500	818	754	2,266	5,763

Numerical variables

	France		Mexico		Spain		UK		USA		All countries	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Amount of emojis	1.84	1.85	0.94	1.41	1.70	2.058	0.62	1.043	0.27	0.592	0.87	1.457
eWOM volume	1.54	2.44	0.67	0.877	1.28	1.996	1.09	5.340	0.37	1.316	0.81	2.460

Note(s): U. = United, C. = COVID-19, SD = Standard deviation, *n* for all countries = 9,329, *n* for France = 1,258, *n* for Mexico = 1,854, *n* for Spai*n* = 1,356, *n* for UK = 1,193, *n* for USA = 3,668

First, we have analyzed the characteristics of our data set. To describe our data, we have divided the study's variables into two categories: categorical and numerical. Table 1 shows the frequencies of emoji presence, the mean (average) of the amount of emojis by tweet, eWOM volume and the frequencies of time frame by country. France and Spain are the countries that most use emojis and the USA is the country that less uses emojis in tweets.

Then, we conducted an exploratory data analysis to check the data distribution of the response variable in the five countries. Table 2 shows the results of the Kolmogorov–Smirnov test, probing that the normality test was significant (all *p*-values are less than 0.01) and that our data is not normally distributed. Considering these results and the research objectives, we have selected the most suitable statistical analysis for testing our hypotheses.

4.1 Testing the hypotheses

4.1.1 Influence of emoji presence, amount of emojis and time frame on eWOM volume. As explained in the methodology section, analyses regression with optimal scaling, using the CATREG algorithm, was used to study the influence of emoji presence, amount of emojis and time frame on eWOM volume. The statistical assumptions of CATREG were checked (predictors = 3, $n = 9{,}329$, $n > 3 + 1$).

Table 2. Test Kolmogorov–Smirnov

Country	Score	Freedom degree	*p*-value
France	0.264	1,258	0.000**
Mexico	0.288	1,854	0.000**
Spain	0.262	1,356	0.000**
UK	0.419	1,193	0.000**
USA	0.389	3,668	0.000**
All countries	0.371	9,329	0.000**

Note(s): ***p*-value < 0.01; **p*-value < 0.05. Null hypothesis = eWOM is normally distributed. *n* for all countries = 9,329, *n* for France = 1,258, *n* for Mexico =1,854, *n* for Spai*n* = 1,356, *n* for UK = 1,193, *n* for USA = 3,668

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Before interpreting the results, we evaluated the intercorrelations among the predictors for both the untransformed and transformed predictors, checking the matrix of correlations and the tolerance before and after the transformation (Appendix). As we expected, multicollinearity is not a concern in this study. In general, a low tolerance is indicative of multicollinearity. The tolerance of all predictors was higher than 0.21, with values above 0.10 (Yang *et al.*, 2022).

According to the results, the regression model with optimal scaling, for the sample that included all countries together (Table 3), was statistically significant (p-value < 0.01). Specifically, the results revealed a highly significant and low correlation (R = 0.197) between eWOM volume and the best combination of emoji presence, amount of emojis and time frame. In total, 3.7% of the variance in eWOM volume is explained by its predictors [R^2 adjusted = 0.037, F (0.961) = 23.590, p-value < 0.01]. According to these statistically highly significant results, emoji presence, amount of emojis and time frame explain the eWOM volume on Twitter in the sample that included all countries together. Thus, we accept *H1*. More specifically the standardized coefficients (Table 3) and the mean graphs (Figure 2) reveal the following:

First, the emoji presence (β = 0.048, e = 0.021, F-value = 5.331, p-value < 0.01) influences positively the eWOM volume, supporting *H1a*. It means that tweets with emojis have more eWOM volume in the sample, including all countries.

Second, the amount of emojis (β = 0.143, e = 0.042, F-value = 11.725, p-value < 0.01) influences the eWOM volume (Table 3). Specifically, the categories with more emojis have more eWOM volume in the sample, including all countries. Therefore, *H1b* has been accepted.

Third, the time frame (β = 0.098, e = 0.011, F-value = 85.544, p-value < 0.01) increases the eWOM volume in the sample that included all countries together, supporting *H1c*. It means that tweets published before the COVID-19 pandemic have more eWOM volume.

4.1.2 Cross-cultural analyses. Regarding a cross-cultural analysis, we run a regression model for each country to test *H2*. First, we have analyzed whether the behavior of the study's variables is different in the five countries' samples. To do the cross-cultural analyses, we followed the previous process. We have divided our variables according to the kind of data into two categories: categorical (emoji presence and time frame) and numerical (amount of emojis and eWOM volume) variables. Then, we have selected the suitable statistical analyses for each kind of data. Specifically, as Table 4 shows, we have run a contingency table analysis to evaluate the differences between groups (countries) in the categorical variables following previous research (Francesco and Roberta, 2019). In this sense, there are highly significant differences between France, Mexico, Spain, the UK and the USA in emoji presence (chi squared = 1333.86, p-value < 0.01) and time frame (chi squared = 707.01,

Table 3. Regression model with optimal scaling

All countries	V. response	R	R^2	R^2 adj.	P. error	F-value
	e-WOM volume	0.197	0.039	0.037	0.961	23.590**
				Standardized coefficients		
	Predictor	Beta	S. Error	Importance	F-value	Significance
	Emoji presence	0.048	0.021	0.148	5.331	0.021**
	Amount of emojis	0.143	0.042	0.619	11.725	0.000**
	Time frame	0.098	0.011	0.234	83.544	0.000**

Note(s): **p-value < 0.01; *p-value < 0.05. Null hypothesis = None of the predictor variables have a statistically significant relationship with the response variable. n for all countries = 9,329

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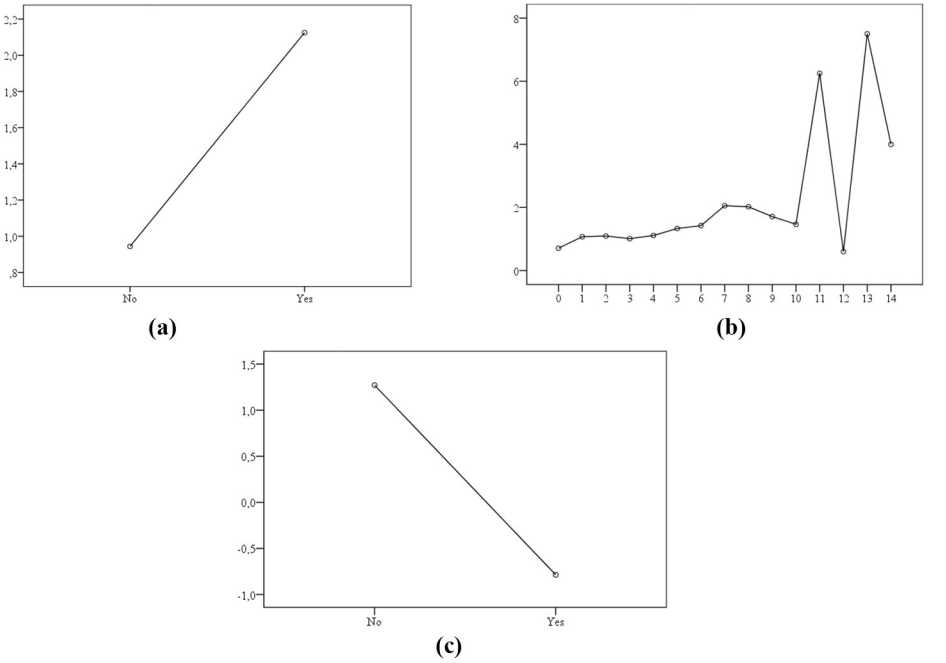

Note(s): (a) Emoji presence; (b) emoji count; (c) time frame

Figure 2. Transformation graphs of eWOM volume according to the emoji presence, the emoji count and the time frame

Table 4. Contingency table analysis

Variable	Chi-square	Degree freedom	*p*-value
Emoji presence	1,333.860	4	0.000**
Time frame	7,07.012	4	0.000**

Note(s): ***p*-value < 0.01; **p*-value < 0.05; Null hypothesis = distribution is equal for the five countries

p-value < 0.01). It means that emoji presence and time frame vary among countries. Thus, *H2*.1a and *H2*.1c have been accepted (Figure 1 and Table 9).

As Table 1 and Figure 3 show, France and Spain use more emojis than the other countries. Comparing the amount of emojis after COVID-19 and before COVID-19, France and Spain have published more tweets with emojis after COVID-19 than tweets without emojis. In addition, Figure 3 shows that only France decreased tweet frequency during the pandemic, whereas the other countries raised it during the same period. Thus, *H2*.1b has been accepted (Figure 1 and Table 9).

Then, we run a Kruskall–Wallis test to evaluate the differences between countries in the numerical variables (Sheraliev and Ślepaczuk, 2023). As Table 5 shows, there are differences between France, Mexico, Spain, the UK and the USA in eWOM volume (*p*-value < 0.01) and amount of emojis (*p*-value < 0.01). Specifically, Figure 4 shows that France and Spain

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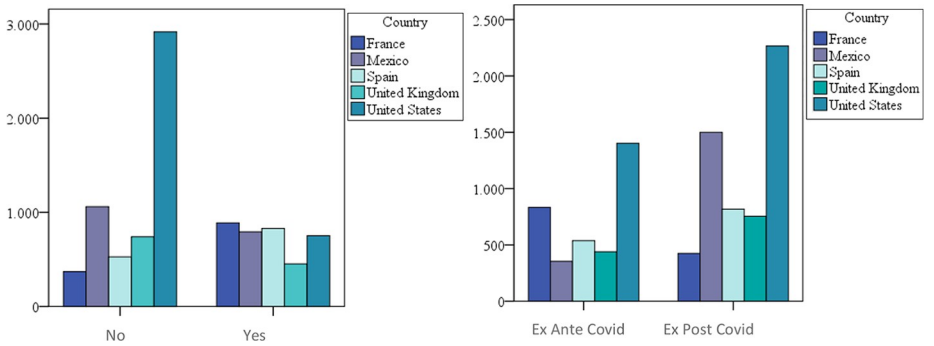
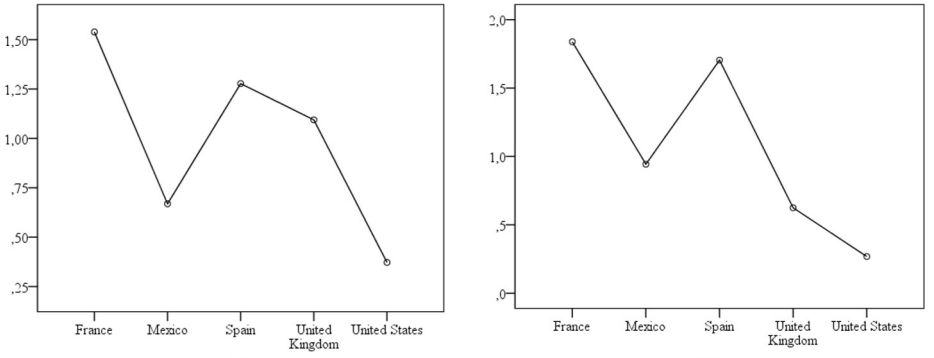


Figure 3. Frequency of tweets with emoji presence and frequency of tweets published before or during pandemic (time frame) by country

Table 5. Kruskall–Wallis test

Variable	*p*-value
eWOM	0.000**
Amount of emojis	0.000**

Note(s): **p-value < 0.01; *p-value < 0.05; Null hypothesis = distribution is equal for the five countries



Note(s): (a) eWOM; (b) amount of emojis

Figure 4. Means for eWOM and amount of emojis by country

behave similarly but differ from the other countries. In detail, France and Spain are the countries with the highest eWOM volume and the highest amount of emojis. Thus, *H2.1d* has been accepted (Figure 1 and Table 9).

The next table (Table 6) shows the results from regression models for each sample to test the specific hypothesis related to *H2.1*. The standardized coefficients (Table 6) and the mean graphs (Figure 5) reveal the following: First, the emoji presence, amount of emojis and time frame explain the eWOM volume on Twitter in the samples from France, the UK, Spain and the USA.

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Table 6. Regression model with optimal scaling

France	V. response	*R*	R^2	R^2 adj.	*P.* error	*F*-value
	e-WOM	0.285	0.081	0.070	0.919	7.313**
				Standardized coefficients		
	Predictor	Beta	S. error	Importance	*F*-value	Significance
	Emoji presence	0.046	0.040	−0.031	1.316	0.251
	Amount of emojis	0.299	0.068	1.006	19.350	0.000**
	Time frame	0.065	0.028	0.027	5.541	0.019*
Mexico	V. response	*R*	R^2	R^2 adj.	*P.* error	*F*-value
	e-WOM	0.066	0.004	0.002	0.996	0.733
Spain	V. response	*R*	R^2	R^2 adj.	*P.* error	*F*-value
	e-WOM	0.153	0.023	0.012	0.977	2.003*
				Standardized coefficients		
	Predictor	Beta	S. error	Importance	*F*-value	Significance
	Emoji presence	0.061	0.033	−0.019	3.405	0.065
	Amount of emojis	0.163	0.023	0.979	50.232	0.001**
	Time frame	0.025	0.022	0.040	1.282	0.258
UK	*V. response*	*R*	R^2	R^2 *adj.*	*P. error*	*F-value*
	e-WOM	0.277	0.077	0.070	0.923	12.297**
				Standardized coefficients		
	Predictor	Beta	S. error	Importance	*F*-value	Significance
	Emoji presence	0.128	0.133	0.024	0.939	0.333
	Amount of emojis	0.132	0.119	0.033	1.232	0.287
	Time frame	0.267	0.028	0.940	92.626	0.000**
USA	V. response	*R*	R^2	R^2 adj.	*P.* error	*F*-value
	e-WOM	0.090	0.008	0.006	0.992	4.275**
				Standardized coefficients		
	Predictor	Beta	S. error	Importance	*F*-value	Significance
	Emoji presence	0.124	0.036	0.674	12.189	0.000**
	Amount of emojis	0.073	0.026	−0.116	8.143	0.000**
	Time frame	0.070	0.018	0.443	16.729	0.000**

Note(s): **p-value < 0.01; *p-value < 0.05. Null hypothesis = None of the predictor variables have a statistically significant relationship with the response variable. *n* for France = 1,258, *n* for Mexico =1,854, *n* for Spain = 1,356, *n* for UK = 1,193, *n* for USA = 3,668

More specifically, the eWOM volume is explained by its predictors in the samples from France with 7.0% of the variance [R^2 adjusted = 0.070, F (0.919) = 7.313, p-value < 0.01], the UK with 7.0% of the variance [R^2 adjusted = 0.070, F (0.923) = 12.297, p-value < 0.01], Spain with 1.2% of the variance [R^2 adjusted = 0.012, F (0.977) = 2.003, p-value < 0.05] and the USA with 0.6% of the variance [R^2 adjusted = 0.006, F (0.992) = 4.275, p-value < 0.01]. However, the sample from Mexico was not statistically significant (p-value > 0.05).

Second, regarding the impact of emoji presence on eWOM volume in each country, the results showed that only in the American sample did emoji presence significantly influence eWOM volume (β = 0.124, e = 0.036, F = 12.189, p < 0.01). This indicates that tweets with emojis generate more eWOM than those without emojis in the American sample. In contrast, emoji presence did not affect eWOM volume in France, Spain or the UK.

Third, regarding the influence of amount of emojis on each country, the results have revealed that this variable affects the eWOM volume in the cases of the French sample (β = 0.299, e = 0.068, F-value = 19.350, p-value < 0.01), the Spanish sample (β = −0.163, e = 0.023, F-value = 50.232, p-value < 0.01) and the American sample (β = 0.073, e = 0.026, F-value = 8.143, p-value < 0.01). In the British sample, the number of emojis does not affect eWOM volume.

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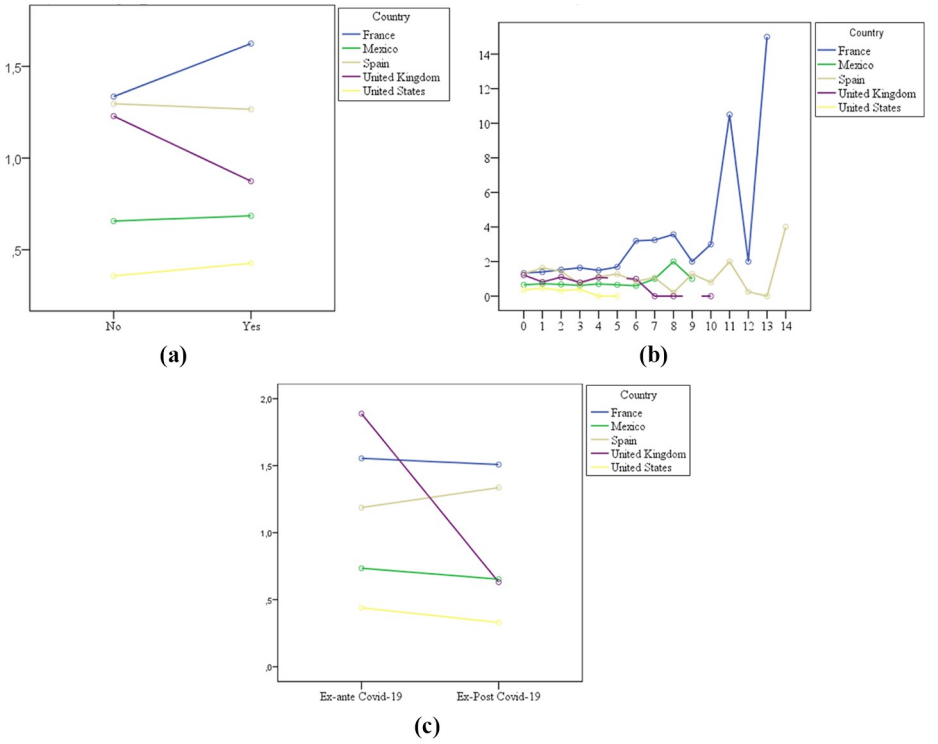

Note(s): (a) Emoji presence; (b) amount of emojis; (c) time frame

Figure 5. Means of eWOM according to the emoji presence, the amount of emojis and the time frame for each country

Fourth, regarding the impact of time frame, the results show that this variable affects eWOM volume in the French (β = 0.065, e = 0.028, F = 5.541, $p < 0.05$), American (β = 0.070, e = 0.018, F = 16.729, $p < 0.01$) and British (β = 0.267, e = 0.028, F = 92.626, $p <$ 0.01) samples. The behavior in France and the USA appears similar (Figure 4), with tweets from both countries published before COVID-19 showing an increase in eWOM volume. In contrast, the British sample shows a stronger and opposite trend, with tweets published after COVID-19 resulting in increased eWOM volume. In the Spanish sample, the time frame did not affect eWOM volume.

Moderation, or interaction, occurs when the effect of X on Y is influenced by W (Hayes and Rockwood, 2017). To test *H2*.2, we examined the interaction between country (our moderator) and predictors (emoji presence, emoji count and time frame) using multiple regression analysis with optimal scaling. We ran seven regression models, including country as an interaction term, one for each predictor and sample (Table 7). This approach identifies whether country moderates the relationship between predictors and eWOM, as shown in previous studies (Wang and Chung, 2020; Hayes and Rockwood, 2017). The results indicate significant differences in most relationships, confirming that country moderates these associations. Only the relationship between time frame and eWOM is similar in France and the USA. Therefore, *H2*.2*b* and *H2*.2c are accepted (Figure 1 and Table 9).

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Table 7. Comparison between countries to identify differences in the relationship studied

	France	Spain	UK
H2. Emoji amount → eWOM			
Spain	0.000**	–	–
USA	0.000**	0.000**	0.000**
H3. Time frame → eWOM			
UK	0.000**	–	–
USA	0.053	–	0.000**

Note(s): Null hypothesis = the relationship is equal in both compared samples; The results are based on regression analyses (optimal scaling). For comparison, all non-significative models and relationships were excluded

Tables 8 and 9 summarize the findings. As can be seen, the totality of hypotheses was accepted in the sample that included all countries together (n = 9,329). However, these relationships were not always significant in the subsamples (France, Mexico, Spain, the UK and the USA).

Our results align with previous studies showing that emojis can increase eWOM on social media (Cavalheiro *et al.*, 2022; Indwar and Mishra, 2022; McShane *et al.*, 2021; Osorio Andrade *et al.*, 2020; Liu and Jansen, 2018b). Specifically, in France and Spain, more emojis led to more retweets (McShane *et al.*, 2021). However, for Mexico, the USA and the UK, the relationship is non-linear, following a "U" shape – more emojis increase eWOM up to a point, after which it decreases. This supports Osorio *et al.*'s (2020) findings that excessive emoji use can overwhelm the message. The cut-off points for these samples are eight for Mexico, six for the UK and three for the USA. These results match Liu and Jansen's (2018a) suggestion of an optimal emoji use level, which varies by country.

Finally, consistent with previous research (Levi *et al.*, 2024; Kejriwal *et al.*, 2021; Li *et al.*, 2019), we conclude that emoji use on Twitter varies by country. Some languages and cultures are more inclined to use emojis (Kejriwal *et al.*, 2021), with the UK showing less emoji usage compared to other samples. As Hall (1976) suggests, high-context cultures (e.g. Spain and Mexico) rely more on contextual cues, which may explain the positive relationship between emoji use and eWOM in the French and Spanish samples. Indwar and Mishra (2022) also found that culture influences how consumers interpret and respond to emojis. For

Table 8. *H1* Specific hypotheses accepted

Variable	*H*	All countries	France	Mexico	Spain	UK	USA
Emoji presence	*H1a*	Accepted	Rejected	Rejected	Rejected	Rejected	Accepted
Amount of emojis	*H1b*	Accepted	Accepted	Rejected	Accepted	Rejected	Accepted
Time frame	*H1c*	Accepted	Accepted	Rejected	Rejected	Accepted	Accepted

Table 9. *H2* Specific hypotheses accepted

	(a) Emoji presence	(b) Emojis amount	(c) Time frame	(d) E-wom
Differences (*H2.1*)	Accepted	Accepted	Accepted	Accepted
Moderation (*H2.2*)	Rejected	Accepted	Accepted	–

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instance, Mexicans are more tolerant of expressive content, leading to a more favorable response to emojis, whereas UK and US consumers, with more restrained preferences, may experience quicker saturation.

5. Conclusions, implications, limitations and future lines

5.1 Conclusions

The aims of this research were, first, to identify if emoji presence, amount of emojis and time frame (posting date ex ante COVID-19 or posting date ex post COVID-19) influence the eWOM volume at ITS organizers on Twitter in five countries. Second, to identify whether there are differences between countries in emoji presence, amount of emojis, time frame and the eWOM volume and moderation by country. The present research extends the digital content marketing literature by studying the emoji influence on eWOM volume in the B2B context in five countries, on Twitter. We tested 22 specific hypotheses (14 of 22 were accepted) (Figure 1).

From a theoretical approach, we can affirm that content quantity is shared in B2B contexts in social media. From a practice approach, we suggest that B2B companies incorporate emojis to drive digital marketing content nationally and globally. In this process, the B2B firms should consider the time frame as a predictor and the culture as the moderator of eWOM volume.

This research highlights the relevance of emoji presence, amount of emojis and time frame (posting date ex ante COVID-19 or posting date ex post COVID-19) in the production of eWOM volume in a social network such as Twitter. The findings show that all predictors positively influence the eWOM volume in B2B contexts. Furthermore, the study confirms the existence of differences between countries in terms of emoji presence, amount of emojis, time frame and eWOM volume.

From a general point of view, the findings show that emoji presence, amount of emojis and time frame explain the eWOM volume on Twitter in the sample that included all countries together (n = 9,329), supporting the emoji effectiveness in the B2B social network communications (Indwar and Mishra, 2022; McShane *et al.*, 2021), contributing with one research related to the use of emojis in the real-world communication context (Bai *et al.*, 2019) in different countries (McShane *et al.*, 2021) and in the business contexts (Indwar and Mishra, 2022). In specific terms, the main contributions to the scientific literature are as follows:

Regarding emoji presence in the sample that included all countries together, the study confirms the effectiveness of emoji presence on eWOM in the business arena (Cavalheiro *et al.*, 2022; Das *et al.*, 2019; McShane *et al.*, 2021; Osorio Andrade *et al.*, 2020). Thus, this research highlights the relevance of emoji presence in the production of eWOM volume in social networks, confirming the power of Twitter to disseminate information (Barhorst *et al.*, 2020); emojis like visual stimuli (Liu and Jansen, 2018b; McShane *et al.*, 2021; Valenzuela-Gálvez *et al.*, 2022); emoji presence in the food and beverages contexts (Jaeger *et al.*, 2017); and emojis in social interactions, stimulating responses from users (Ge and Gretzel, 2018).

Regarding the amount of emojis in the sample that included all countries together, the results support that the amount of emojis in a tweet is relevant to produce eWOM volume (McShane *et al.*, 2021). From a general point of view, it was found that the more emojis a tweet has, the more retweets it will have (McShane *et al.*, 2021; Osorio Andrade *et al.*, 2020) confirming the effects of different amounts of emoji in a message (Das *et al.*, 2019; Osorio Andrade *et al.*, 2020). In sum, For French and Spanish samples, more emojis are associated with more retweets. However, this relationship was non-linear for Mexico, the USA and the UK, where eWOM increased with emojis up to a point before decreasing. The cut-off points were eight emojis for Mexico, six for the UK and three for the USA.

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Regarding the time frame in the sample that included all countries together, the study confirms the effectiveness of the time frame to increase the eWOM volume, given that the number of emojis per tweet changed due to COVID-19 pandemic confirming previous research (Das, 2021). Specifically, tweets published before the pandemic COVID-19 have more eWOM volume; on the contrary, the number of emojis decreased ex post COVID-19 (Liu *et al.*, 2022).

Regarding the cross-cultural approach, from a general point of view, the results confirm the differences by country between emoji presence, emoji quantity, time frame and eWOM volume on Twitter. Thus, even emojis cross borders (Kerslake and Wegerif, 2017) in the business domain and influence the use of social networks by companies (Dwivedi *et al.*, 2021); the specific context or culture influences the results of this nonverbal communication. Specifically, the UK used less emoticons than other samples.

Our study also found a country-moderating effect on almost all (except one) significant relationships. This country's interaction was statistically significant. This means that the effect of emoji amount and time frame on eWOM varies among the five regions analyzed: France, Mexico, Spain, the UK and the USA. Only eWOM in France and the USA behaved similarly during the pandemic (both showed less eWOM than before).

Only in the USA sample, all predictors (emoji presence, number of emojis and time frame) had a significant influence on eWOM volume, even though the US sample had the least emoji presence, only 21% of tweets had emojis. In the case of the French sample, two predictors significantly influenced the eWOM volume, the number of emojis and the time frame. However, in two countries, only one predictor influences eWOM volume: in the case of the Spain sample, it was the number of emojis, and in the case of the UK sample, it was the time frame.

Regarding the time frame, the behavior of France and the USA were similar; that is, tweets published during the COVID-19 period increased the eWOM volume. However, only France reduced its tweet frequency during the pandemic, whereas the other countries increased theirs. In contrast, the British sample shows a stronger, opposite trend, with tweets published after COVID-19 resulting in higher eWOM volume.

Generally, we can conclude that emoji presence, amount of emojis and time frame are relevant predictors of eWOM volume in B2B contexts. Nevertheless, the culture moderates the eWOM volume behavior in each country (Dang and Raska, 2021). Specifically, in the business field, culture impacts how companies use social networks (Dwivedi *et al.*, 2021) and affects eWOM volume. More importantly, the country's influence is significant in B2B contexts. These findings highlight the effectiveness of emojis in driving eWOM in B2B settings. More specifically, the country's moderation is significant in B2B contexts. Overall, these findings demonstrate the usefulness of emojis in generating eWOM in B2B contexts.

5.2 Implications

At a general level, the results show that B2B companies should integrate emojis into social media communications, given the effectiveness of the presence of emojis and quantity on the eWOM volume production (Indwar and Mishra, 2022; McShane *et al.*, 2021), confirming the usefulness of social networks to promote ITSs (Lapoule and Rowell, 2016).

Regarding the presence and quantity of emojis, our results suggest that it is useful to introduce emojis into messages on Twitter, at least up to a certain quantity that varies between countries. Specifically, more emojis are always merrier for French and Spanish audiences. However, there are thresholds beyond emojis becoming less effective for Mexico (six), the UK (six) and the USA (three). These findings are helpful for practitioners.

In terms of the time frame, it was found that it is significant to the production of eWOM for France, the UK and the USA, but its effects differ among regions. Specifically, only France and the USA behaved similarly during the pandemic, but other relationships changed

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Table 10. Conclusions and theoretical and managerial implications

Conclusions	Theoretical and managerial implications
Emoji presence, the quantity of emojis and the time frame (before and after COVID-19) significantly influence eWOM (electronic word-of-mouth) volume on Twitter in B2B contexts. The presence of emojis acts as a visual stimulus that effectively engages users and increases content dissemination. Cultural differences across countries significantly moderate the effects of emoji usage and the time frame on eWOM volume The relationship between the number of emojis and eWOM volume varies among countries The time frame significantly affects eWOM volume. Tweets published before the pandemic generally had higher eWOM volumes, but countries such as France and the USA saw increased eWOM for tweets during the pandemic. In contrast, emoji usage decreased post-COVID-19	Theoretical implications: The findings confirm the theoretical validity of incorporating emojis in B2B social media communications to enhance eWOM The effectiveness of emojis varies across countries and cultures, underscoring the importance of considering regional differences in digital marketing strategies. This aligns with existing literature emphasizing culture's role in moderating communication outcomes The significance of the time frame (e.g. pre- and post-COVID-19) highlights the importance of context in communication strategies. This suggests that external factors, like global crises, can alter audience behavior and response patterns Managerial implications: Practitioners should integrate emojis in their Twitter communications while being mindful of cultural thresholds. B2B marketers should adapt their strategies during crises like COVID-19 by leveraging audience preferences for face-to-face interactions and understanding shifts in digital engagement behavior to maintain eWOM effectiveness

depending on the sample. This means that considering differences by time frame (the context in which communication occurs), culture and country is very important for increasing the effectiveness of strategies on Twitter. The results showed that a crisis like COVID-19 hurts eWOM in many countries. As COVID-19 stages also hide other variables (such as the differences between formats, presence vs online and the use of different strategies to approach audiences), these hidden factors could explain the results. In this sense, the data could suggest that ITS clients prefer face-to-face trade shows.

5.3 Limitations and future lines

The data was carefully collected, coded and analyzed in our study. Our findings are valid and other authors can replicate the study. However, our research also has limitations. The main limitation is that only one industry and one social network were analyzed. Consequently, the findings should not be generalized to contexts with different settings from this study. We suggest new studies applied across diverse sectors, platforms and countries. Finally, the usage of emojis in other B2B firms can be studied.

Furthermore, Table 10 illustrates conclusions, theoretical and managerial implications.

References

Almaguer, J., Felix, R. and Harmeling, C.M. (2024), "Emoji marketing: toward a theory of brand paralinguistics", *International Journal of Research in Marketing*, Vol. 42 No. 1.

Babić Rosario, A., de Valck, K. and Sotgiu, F. (2020), "Conceptualizing the electronic word-of-mouth process: what we know and need to know about eWOM creation, exposure, and evaluation", *Journal of the Academy of Marketing Science*, Vol. 48 No. 3, pp. 422-448.

Bai, Q., Dan, Q., Mu, Z. and Yang, M. (2019), "A systematic review of emoji: current research and future perspectives", *Frontiers in Psychology*, Vol. 10, p. 2221.

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Balaji, M.S., Behl, A., Jain, K., Baabdullah, A.M., Giannakis, M., Shankar, A. and Dwivedi, Y.K. (2023), "Effectiveness of B2B social media marketing: the effect of message source and message content on social media engagement", *Industrial Marketing Management*, Vol. 113, pp. 243-257.

Barhorst, J.B., Wilson, A. and Brooks, J. (2020), "Negative tweets and their impact on likelihood to recommend", *Journal of Business Research*, Vol. 117, pp. 727-739.

Cavalheiro, B.P., Prada, M., Rodrigues, D.L., Garrido, M.V. and Lopes, D. (2022), "With or without emoji? Perceptions about emoji use in different brand-consumer communication contexts", *Human Behavior and Emerging Technologies*, Vol. 2022, pp. 1-8.

Chakraborty, K., Bhatia, S., Bhattacharyya, S., Platos, J., Bag, R. and Hassanien, A.E. (2020), "Sentiment analysis of COVID-19 tweets by deep learning classifiers—a study to show how popularity is affecting accuracy in social media", *Applied Soft Computing Journal*, Vol. 97, pp. 1-14.

Crowe, A. (2012), "Disasters 2.0: the application of social media systems for modern emergency management".

Cummings, S. and O'Neill, M. (2021), "The impact of COVID-19 on B2B marketing: an exploratory study", *Marketing Intelligence and Planning*, Vol. 39 No. 4, pp. 423-432.

Dang, A. and Raska, D. (2021), "National cultures and their impact on electronic word of mouth: a systematic review", *International Marketing Review.*

Das, A. (2021), "How has the coronavirus (COVID-19) pandemic affected global emoji usage?" *Journal of Human Behavior in the Social Environment*, Vol. 31 Nos 1/4, pp. 425-434.

Das, G., Wiener, H.J.D. and Kareklas, I. (2019), "To emoji or not to emoji? Examining the influence of emoji on consumer reactions to advertising", *Journal of Business Research*, Vol. 96, pp. 147-156.

Donthu, N., Kumar, S., Pandey, N., Pandey, N. and Mishra, A. (2021), "Mapping the electronic word-of-mouth (eWOM) research: a systematic review and bibliometric analysis", *Journal of Business Research*, Vol. 135, pp. 758-773.

Dwivedi, Y.K., Ismagilova, E., Rana, N.P. and Raman, R. (2021), "Social media adoption, usage and impact in business-to-business (B2B) context: a state-of-the-art literature review", *Information Systems Frontiers*.

Dwivedi, Y.K., Ismagilova, E. and Wang, Y. (2021), "Setting the future of digital and social media marketing research: perspectives and research propositions", *International Journal of Information Management*, Vol. 59, p. 102168.

Francesco, G. and Roberta, G. (2019), "Cross-country analysis of perception and emphasis of hotel attributes", *Tourism Management*, Vol. 74, pp. 24-42.

Ge, J. and Gretzel, U. (2018), "Emoji rhetoric: a social media influencer perspective", *Journal of Marketing Management*, Vol. 34 Nos 15/16, pp. 1272-1295.

Geldres-Weiss, V.V., Arcos-Pino, N.B., Geldres-Weiss, S.L. and Guerrero-Stuardo, P.E. (2021), "Destination country and export performance of agri-food products during the COVID-19 crisis", *International Journal of Export Marketing*, Vol. 4 No. 3, p. 208.

Gifi, A. (1990), *Nonlinear Multivariate Analysis*, Wiley-Blackwell, London.

Hall, E.T. (1976), *Beyond Culture*, Anchor Press.

Hartmann, A., van der Kooij, A.J. and Zeeck, A. (2009), "Exploring nonlinear relations: models of clinical decision making by regression with optimal scaling", *Psychotherapy Research*, Vol. 19 Nos 4/5, pp. 482-492.

Hayes, A.F. and Rockwood, N.J. (2017), "Regression-based statistical mediation and moderation analysis in clinical research: observations, recommendations, and implementation", *Behaviour Research and Therapy*, Vol. 98, pp. 39-57.

Hollebeek, L. and Macky, K. (2019), "Digital content marketing's role in fostering consumer engagement, trust, and value: framework, fundamental propositions, and implications", *Journal of Interactive Marketing*, Vol. 45 No. 1, pp. 27-41.

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Holliman, G. and Rowley, J. (2014), "Business to business digital content marketing: marketers' perceptions of best practice", *Journal of Research in Interactive Marketing*, Vol. 8 No. 4, pp. 269-293.

Indwar, R.G. and Mishra, A.S. (2022), "Emojis: can it reduce post-purchase dissonance?" *Journal of Strategic Marketing*, Vol. 31 No. 4, p. 2013935.

Jaeger, S.R., Vidal, L., Kam, K. and Ares, G. (2017), "Can emoji be used as a direct method to measure emotional associations to food names? Preliminary investigations with consumers in USA and China", *Food Quality and Preference*, Vol. 56, pp. 38-48.

Kabadayi, S., O'Connor, G.E. and Tuzovic, S. (2020), "Viewpoint: the impact of coronavirus on service ecosystems as service mega-disruptions", *Journal of Services Marketing*, Vol. 34 No. 6, pp. 809-817.

Kejriwal, M., Wang, Q., Li, H. and Wang, L. (2021), "An empirical study of emoji usage on twitter in linguistic and national contexts", *Online Social Networks and Media*, Vol. 24, p. 100149.

Kerslake, L. and Wegerif, R. (2017), "The semiotics of emoji: the rise of visual language in the age of the internet", *Media and Communication*, Vol. 5 No. 4, pp. 75-78.

Kim, E., Sung, Y. and Kang, H. (2014), "Brand followers' retweeting behavior on twitter: how brand relationships influence brand electronic word-of-mouth", *Computers in Human Behavior*, Vol. 37, pp. 18-25.

Kooij, A. J. V D. (2007), "Prediction accuracy and stability of regression with optimal scaling transformations", Leiden University, available at: https://hdl.handle.net/1887/12096

Krejtz, K. and Borkowski, K. (2020), "The role of culture in the use of emojis in marketing communications", *Journal of Business Research*, Vol. 119, pp. 504-511.

Lapoule, P. and Rowell, J. (2016), "Using social media to support trade shows: developing the capabilities", *South Asian Journal of Business and Management Cases*, Vol. 5 No. 1, pp. 88-98.

Leek, S., Houghton, D. and Canning, L. (2019), "Twitter and behavioral engagement in the healthcare sector: an examination of product and service companies", *Industrial Marketing Management*, Vol. 81, pp. 115-129.

Levi, S., Hauthal, E., Mukherjee, S. and Ostermann, F.O. (2024), "Visualizing emoji usage in geo-social media across time, space, and topic", *Frontiers in Communication*, Vol. 9, p. 1303629.

Li, M., Chng, E., Chong, A.Y.L. and See, S. (2019), "An empirical analysis of emoji usage on twitter", *Industrial Management and Data Systems*, Vol. 119 No. 8, pp. 1748-1763.

Liu, Y. and Jansen, B.J. (2018a), "The role of emojis in social media: a content analysis of emoji use on twitter", *Computers in Human Behavior*, Vol. 85, pp. 259-268.

Liu, Z. and Jansen, B.J. (2018b), "Questioner or question: Predicting the response rate in social question and answering on Sina Weibo", *Information Processing and Management*, Vol. 54 No. 2, pp. 159-174.

Liu, C., Tan, X., Zhou, T., Zhang, W., Liu, J. and Lu, X. (2022), "Emoji use in China: popularity patterns and changes due to COVID-19", *Applied Intelligence*.

Luangrath, A.W., Peck, J. and Barger, V. (2022), "Textual paralanguage and its implications for marketing communications", *Journal of Marketing*, Vol. 86 No. 1, pp. 87-108.

McShane, L., Pancer, E., Poole, M. and Deng, Q. (2021), "Emoji, playfulness, and brand engagement on twitter", *Journal of Interactive Marketing*, Vol. 53 No. 1, pp. 96-110.

Mladenović, D., Koštiál, K., Ljepava, N., Částek, O. and Chawla, Y. (2023), "Emojis to conversion on social media", *International Journal of Consumer Studies*, Vol. 47 No. 3, pp. 977-994.

Osorio Andrade, C.F., Peláez Muñoz, J. and Rodríguez Orejuela, A. (2020), "Cantidad adecuada de emojis y caracteres para generar eWOM en Facebook", *Suma de Negocios*, Vol. 11 No. 24, pp. 24-23.

Downloaded from http://www.emerald.com/sjme/article-pdf/30/1/99/11219775/sjme-05-2024-0122en.pdf by Universitat de Valencia user on 11 February 2026

Petty, R.E. and Cacioppo, J.T. (1986), "The elaboration likelihood model of persuasion", Springer, New York, pp. 1-24.

Pereira, F.R. and D'Urso, S. (2021), "The impact of emoji use on consumer engagement in social media: an analysis of the effects of emoji quantity", *Computers in Human Behavior*, Vol. 120, p. 106747.

Phua, J., Jin, S.V. and Kim, J.(J.). (2017), "Gratifications of using Facebook, Twitter, Instagram, or Snapchat to follow brands: the moderating effect of social comparison, trust, tie strength, and network homophily on brand identification, brand engagement, brand commitment, and membership intention", *Telematics and Informatics*, Vol. 34 No. 1, pp. 412-424.

Pınarbaşı, F. and Kırçova, İ. (2021), "Emoji usage in brand communication through social media: an evaluation on Turkey context", *Turkish Journal of Marketing*, Vol. 6 No. 1, pp. 90-103.

Rivadeneira, L., Yang, J.B. and López-Ibáñez, M. (2021), "Predicting tweet impact using a novel evidential reasoning prediction method", *Expert Systems with Applications*, Vol. 169, p. 114400.

Sharma, P., Leung, T.Y., Kingshott, R.P.J., Davcik, N.S. and Cardinali, S. (2020), "Managing uncertainty during a global pandemic: an international business perspective", *Journal of Business Research*, Vol. 116, pp. 188-192.

Sheraliev, I. and Ślepaczuk, R. (2023), "Cross-country differences in return and volatility metrics of world equity indices", *Central European Economic Journal*, Vol. 10 No. 57, pp. 90-115.

Singh, J., Shukla, P. and Kalafatis, S.P. (2017), "IT usage for enhancing trade show performance: evidence from the aviation services", *Journal of Business and Industrial Marketing*, Vol. 32 No. 3, pp. 398-408.

Soboleva, A., Burton, S., Mallik, G., Khan, A. (2017), "Retweet for a chance to…': an analysis of what triggers consumers to engage in seeded eWOM on Twitter", *Journal of Marketing Management*, Vol. 33 Nos 13/14, pp. 1120-1148.

Son, J., Lee, H.K., Jin, S. and Lee, J. (2019), "Content features of tweets for effective communication during disasters: a media synchronicity theory perspective", *International Journal of Information Management*, Vol. 45, pp. 56-68.

Sridevi, P., Niduthavolu, S. and Vedanthachari, L.N. (2020), "Analysis of content strategies of selected brand tweets and its influence on information diffusion", *Journal of Advances in Management Research*, Vol. 18 No. 2, pp. 227-249.

Valenzuela-Gálvez, E.S., Garrido-Morgado, A. and González-Benito, Ó. (2022), "Boost your email marketing campaign! Emojis as visual stimuli to influence customer engagement", *Journal of Research in Interactive Marketing*.

Villamediana, J., Küster, I. and Vila, N. (2019), "Destination engagement on Facebook: time and seasonality", *Annals of Tourism Research*, Vol. 79, p. 102747.

Wang, C.L. and Chung, H.F. (2020), "Business networking and innovation of Asian enterprises in Western countries: the moderation of institutional distance", *Industrial Marketing Management*, Vol. 88, pp. 152-162.

Wang, Y. and Wang, C. (2022), "The influence of cultural context on emoji effectiveness in online marketing: a cross-cultural study", *International Journal of Advertising*, Vol. 41 No. 1, pp. 77-99.

Yang, Q., Nan, Z. and Tang, Z. (2022), "Influencing factors of the grassland ecological compensation policy to herdsmen's behavioral response: an empirical study in HEXI corridor", *Acta Ecologica Sinica*, Vol. 42 No. 2, pp. 74-79.

Ye, Q. and Ho, K. (2023), "The changing landscape of digital marketing communication during the COVID-19 pandemic", *Journal of Business Research*, Vol. 142, pp. 198-210.

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Appendix

Table A1. Evaluation of intercorrelations among the predictors

	Correlation and tolerance					
	Correlations				Tolerance	
	Zero order	Partial	Semipartial	Importance	After transformation	Before transformation
Model 1 (All countries)						
Emoji presence	0.120	0.040	0.039	0.148	0.672	0.464
Emoji count	0.168	0.119	0.117	0.619	0.676	0.466
Time frame	0.092	0.100	0.098	0.234	0.994	0.988
Model 2 (France)						
Emoji presence	−0.054	0.044	0.043	−0.031	0.856	0.586
Emoji count	0.273	0.278	0.277	1.006	0.863	0.590
Time frame	0.033	0.066	0.064	0.027	0.970	0.974
Model 3 (Mexico)						
Emoji presence	0.019	0.020	0.020	0.089	0.952	0.406
Emoji count	0.051	0.048	0.048	0.573	0.976	0.403
Time frame	0.037	0.040	0.040	0.344	0.974	0.966
Model 4 (Spain)						
Emoji presence	−0.007	0.057	0.056	−0.019	0.831	0.565
Emoji count	0.141	0.148	0.148	0.979	0.832	0.559
Time frame	0.037	0.025	0.025	0.040	0.978	0.972
Model 5 (UK)						
Emoji presence	0.014	0.057	0.054	0.024	0.180	0.391
Emoji count	0.019	0.058	0.056	0.033	0.180	0.390
Time frame	0.270	0.267	0.267	0.940	0.997	0.990
Model 6 (USA)						
Emoji presence	0.044	0.070	0.070	0.674	0.318	0.206
Emoji count	−0.013	0.042	0.042	−0.116	0.328	0.211
Time frame	0.051	0.067	0.067	0.443	0.920	0.920

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