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Article

Social Networks in Military Powers: Network and Sentiment Analysis during the COVID-19 Pandemic

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Abstract: The outbreak of the COVID-19 pandemic shifted socialization and information seeking to social media platforms. The armed forces of the major military powers initiated civil support operations to combat the invisible and common enemy. The aim of this study is to analyze the existence of differential behavior in the corporate profiles of the major military powers on Twitter, Instagram, and Facebook during the COVID-19 pandemic. The principles of social network analysis were followed, along with sentiment analysis, to study web positioning and the emotional content of the posts (N = 25,328). The principles of data mining were applied to process the KPIs (Fanpage Karma), and an artificial intelligence (meaning cloud) sentiment analysis was applied to study the emotionality of the publications. The analysis was carried out using the IBM SPSS Statistics 25 statistical software. Subsequently, a qualitative content analysis was carried out using frequency graphs or word clouds (the application “nubedepalabras” used in English). Significant differences were found between the behavior on social media and the organizational and communicative culture of the nations. It is highlighted that some nations present different preferences from the main communicative strategy developed by their armed forces. Corporate communication of the major military powers should consider the emotional nature of their posts to align with the preferences of their population.

Keywords: COVID-19; social media platforms; armed forces; communicative strategy; corporate communication

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1. Introduction

On 11 March 2020, the WHO made the assessment that COVID-19 could be characterized as a pandemic. This situation produced a strong impact on human activity at the international level [1]. International communities needed to work jointly to fight against a common biological enemy—COVID-19 [2].

In this way, states organized a series of strategies aimed at protecting society, with two of the most used being home confinement [3] and support operations for civilian populations through their armies. These armed forces, in response to society’s perception of insecurity and vulnerability, developed communicative strategies based on responsibility, agility, innovation, and resilience. Traditional leadership was no longer effective, and social needs required comprehensive sustainable leadership [4] from a socially legitimate actor who inspired trust. The current perspective is focused on positive leadership (positive moral perspective, leader’s self-awareness, positive behavior modeling for followers, personal and social identification of followers with the leader and the group, and positive social exchanges between the leader and followers), introduced by Luthans [5] from positive organizational psychology [6,7], promoting well-being and organizational and work-related health [8].

A positive leader is a guiding leader who first self-leads and then leads others (self-leadership, self-awareness, self-control, social awareness, and relationship management), enhancing engagement; creating an optimal and functional work environment; and promoting respect, equity, and integration on a cooperative basis to manage social systems.

During home confinement, human communication and interaction turned to technology, causing an increase in the use of social networks as an information and social channel, since it allowed for coping with mourning, loneliness, and fear [9]. Most individuals found social media to be a means to obtain the interaction and social support necessary for them [10]. Social media provided an open window to the world inside our houses, allowed us to communicate and remain socially connected despite lockdown, and provided us with up-to-the-minute monitoring of developments to the pandemic [11].

Another international strategy aiming to protect society during this period was support operations for civilian populations through armies [12,13]. The social media accounts of these units involved reporting on the evolution of their deployment, received the support of Internet users, as well as served as a space for debate on their opinions of the situation caused by the pandemic [14].

In this vein, the communicative strategies of armed forces involved the population through a set of principles [15]: (a) demonstrating social responsibility (SR) by fostering dialogue with members or showcasing the institution as a responsible citizen, (b) promoting community by encouraging volunteering or engaging in philanthropy, and (c) coordinating the community to facilitate gatherings and group activities.

2. Theoretical Background

2.1. The Army as an Organization on Social Media

Strategic narratives provided through the social media profiles of the armed forces convey not only information but also deeper elements of the socialization process inherent in human groups, such as feelings and thoughts, with a persuasive function included in communication [16]. Communication is more than just language and the relationship between sender and receiver. Communication has a component of culture, intersubjectivity, and interrelationship. Words have infinite power, and organizations have a strategy in the way discourse can seduce members of a population. The concept of public opinion is introduced as a key informative element in the globalized and interconnected world [17]. This element is sensitive in social media, and as philosopher Habermas [18] points out, it can be manipulated, distorted, and predetermined and can alter the axis of social cohesion and influence processes of political construction and legitimation. It is legitimate to question what role communication should play in a changing and vulnerable social environment and how it can be used as a tool for the defense of the State. The presence of new threats, such as the COVID-19 pandemic, offers armies and states a new strategic doctrine for defense against a common enemy (COVID-19), to be fought not only in physical space but also in the attitudinal realm (cognition, behavior, and emotion) in a global cyberspace context (social media) [19]. In this context, strategic communication [20] is conceptualized as a means and instrument of power that helps defend national interests [21].

The management of digital communication by institutions [22] evolves and adapts to the networked society [23] between armed institutions and their audiences. Cerezo [24] explained how organizations must strategically include social media in communication management. In this sense, communication in the armed forces is highly developed and is a key element in their work related to public opinion. All communication offices belong to the cabinets of the different chiefs of staff, and therefore, their actions are considered strategic [14].

The COVID-19 pandemic has led the military to engage with society by showcasing their dedication to humanitarian operations, security operations, citizen welfare, evacuation, and rescue operations while still conveying symbols of the nation, military spirit, professional competence, military discipline, command, and combat operations [25]. From this perspective, strategic corporate communication and message management are required to contribute to strengthening the image and reputation of the military entity, helping to position a positive image in both internal and external corporate communication, in line with the mission and vision of the armed forces [25].

Corporate communication is strongly influenced by the context and organizational culture and, fundamentally, it is group communication [26,27]. The culture of a group is defined by people's understanding of the social system to which they belong [28,29]. According to Rincón [30], corporate communication originates from an organized process in which people, processes, and organizational structure come together with the intention of leaving a mark on the organization based on factors of conceptual identity, vision, and behavior. Emphasis is placed on the importance of establishing an organizational nomenclature or code based on its nature and corporate purpose, which stimulates all organizational actions, creating a conducive corporate concept for projecting a global image. Additionally, a key function, within the strategic framework of intelligent organizations, is empathy and the alignment of corporate identity, image, reputation, social values, differentiating characteristics, and competitive strategies. Ulloa et al. [31] highlighted an instrumental perspective in corporate communication, the institution's effectiveness based on the proper management of organizational information, as well as the creation of symbolic universes and all kinds of languages in line with the demands of the industry and the public. Cordón-Benito et al. [32] emphasizes the role of corporate communication in dialogue management to regain trust and to overcome cultural barriers.

Kruckeberg and Starck [33] explained how, in an increasingly globalized and multicultural environment, the sense of community is diluted to the detriment of a society that is becoming more homogeneous and standardized. Corporate communication professionals are responsible for achieving understanding between cultures without losing identity, reclaiming communities, and alleviating the feeling of anonymity or lack of identity in society. In addition, the theory of social identity (TIS) by Tajfel and Billig [34] states that simple categorization is sufficient to produce out-group discrimination. Empirical evidence derived from the minimal group paradigm suggests that the mere social categorization of individuals leads to ingroup favoritism and social competition with the out-group category [34]. This socio-cognitive view of explaining intergroup relationships is essential to understand how, from simple categorization, the identity of different countries can lead to conflict instead of fostering cooperation. Corporate social responsibility can promote corporate identity that enhances cooperation rather than conflict.

2.2. Social Media Analysis in the Liquid Society

The virtual world is essentially the blurring of boundaries from the tangible world, reproducing a series of cultural aspects of the postmodern or liquid society in Bauman's terms [35,36]. The postmodern liquid society [37] is characterized by its immediacy and a high degree of theatricality on social media, understanding this as a performance where it becomes difficult to distinguish reality from fiction. One of its main features is the theatricalization of reality with a strong emotional component, where emotions are heightened or, in popular terms, "it is just a drama" [38]. Drama, as defined by Marwick and Boyd [38], is "interpersonal conflict that takes place in front of an active, engaged audience, often on social media". Therefore, the posts that receive the most likes are those that evoke basic emotions [39]. In this way, reality and fiction merge, generating a new concept of social community and new social rules of communication. Despite the critical focus on "the drama" and the possibility of encouraging social movements or good practices such as mental health [40], social media posts portray a bucolic world with an idealized vision [41]. It is common to find that posts with the highest number of likes, comments, and reactions are those that present a positive polarity and subjectivity [42,43]. In other words, they are cheerful posts that depict pleasant and amiable situations, where influencers share their personal views. However, there are differences depending on the topics. Posts related to body image, self-expression, travel, digital culture, and startups are associated with positive polarity, while depression, loneliness, and relationship breakdowns are associated with negative polarity [44].

The traditional social media platforms are Twitter, Instagram, and Facebook, and although they share common features such as immediacy and user interaction, each has its own characteristic profile [45]. Specifically, Twitter is a space for criticism, Instagram is a showcase for self-presentation, and Facebook revives the notion of community and closeness despite physical distance [45].

During this period, the most used social media platforms were Facebook and Instagram among Millennials (born between 1980) [46]. Generation Z (born in 1996 onwards) showed a preference for platforms such as Instagram and Twitter to receive and share information, images, videos, opinions, and personal experiences related to COVID-19 [47]. On the other hand, Facebook is a highly impactful social media platform with a large number of users and followers, including a wider age range than other platforms [14].

Social media channels generate a large amount of data, offering valuable information for understanding the virtual ecosystem [48,49]. Thus, each posted content generates a set of aggregated expressions that analyze its performance, popularly known as key performance indicators (KPIs) [50,51]. Therefore, it is necessary to have a methodological design that allows for the capture and analysis of posts and their respective KPIs. However, a strictly KPI-based approach would not allow us to understand the relationship between the linguistic and psychological nature of the post and its web positioning. Therefore, it is necessary to apply artificial intelligence (AI) to analyze the nature of a large amount of text. The application of sentiment analysis, a well-known technique, allows us to analyze the emotional content of natural language text [52]. It enables the evaluation of polarity (whether it is positive or negative), as well as elements such as subjectivity and irony [45,53]. These models are primarily based on Plutchik's Wheel, a psychological theory of emotions [54].

The purpose of the current research was to analyze the existence of differential behavior in the corporate profiles of the main military powers on the social networks Twitter, Instagram, and Facebook during the COVID-19 pandemic. This main objective is divided into several specific ones: (a) to analyze the existence of differences between nations in terms of key performance indicators (KPI) and sentiment analysis; (b) to study Twitter, Instagram, and Facebook differentially; and (c) to determine which variables moderate success (number of likes of a publication) in each nation.

Thus, hypotheses have been proposed:

H1. *There are differences in key performance indicators and the sentiment analysis between nations.*

H2. *The social networks Twitter, Instagram, and Facebook behave differently in terms of key performance indicators (KPI) and sentiment analysis.*

H3. *The success of a publication (measured by the number of likes) depends on the culture of each nation and the differential behavior of each social network.*

3. Materials and Methods

3.1. Universal Sample

The sample corpus was initially composed of N = 30,727 posts distributed across the social networks Twitter (N = 18,517), Instagram (N = 3589), and Facebook (N = 8621). The sample-filtering procedures, in which posts without text (impossible to perform a sentiment analysis) and posts that were unrecoverable were eliminated, reducing the sample to 25,328 (see Table 1).

Table 1. The sample corpus.

Country	Twitter	Instagram	Facebook	Total
Germany	2353	220	209	2782
Saudi Arabia	101	0 *	251	352
Australia	309	275	322	906
Canada	594	256	897	1747
Japan	318	0 *	225	543
Korea	44	0 *	252	296
Poland	2188	0 *	762	2950
Russia	2496	357	2141	4994
USA	1383	695	1320	3398
Israel	333	273	298	904
Italy	177	358	397	932
India	775	630	701	2106
France	1421	323	554	2298
UK	625	202	292	1119
Total	13,117	3589	8621	25,327

* Note: 0 values indicate there is no Instagram channel for theses dates.

The corporate profiles of the armies of the following powers were analyzed: Germany, Saudi Arabia, Australia, Canada, Japan, Korea, Poland, Russia, the United States, Israel, Italy, India, France, and the United Kingdom. The distribution of the sample is presented in Table 1. It should be noted that the number of posts is related to the activity of the profile, with diversity in the number of posts published between nations (see Table 1).

These nations were selected on the basis of their economic investment into defense according to the STATISTA database.

3.2. Design and Process

The research design was based on network analytics, a methodology that brings together a series of techniques that allow for both data collection and data processing. Thus, this research is made up of a series of key steps: monitoring and data collection, analysis and processing of key performance indicators, sentiment analysis, and qualitative content analysis.

(a) Monitoring and data collection

The procedure for capturing and monitoring publications and their corresponding key performance indicators (KPIs) [51] was carried out using the FanpageKarma software. This allows for the monitoring of different channels, as well as the downloading of publications and their key performance indicators: likes, number of comments, interactions, etc. This procedure manages to resolve the technical and methodological difficulties exposed in research of a similar nature [14].

(b) Analysis and treatment of key performance indicators

The amount of data obtained on key performance indicators of the collected publications involved processing the initial database using what is known as data mining [55], with the main purpose of locating publications that were not retrievable or visible in the profiles, as well as publications lacking text. Similarly, it was realized that the data were not very normotypical in nature. The maximums that were found were viral posts, which were of a different nature. A total of 1133 viral posts were found.

(c) Sentiment analysis

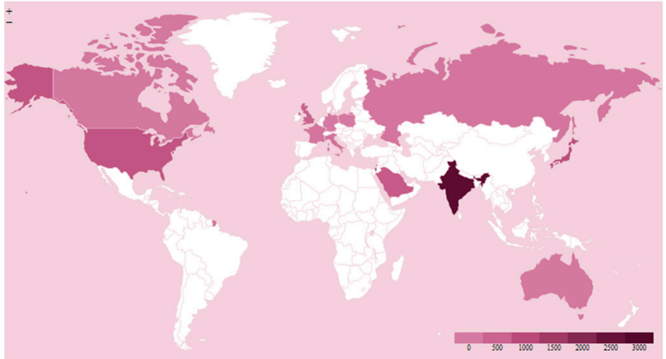
A sentiment analysis was carried out using the Meaning Cloud software and the "Emotion Recognition" package in its demo version. This allowed the analysis to be carried out for texts in English, French, and Italian. Posts made in languages that were not available, such as Arabic, Russian, Polish, German, Japanese, and Korean, were translated into English. They were then analyzed. This software has an advantage over others in that it offers a percentage of confidence in the reliability of its analysis. As shown in Figure 1f, all nations obtained average percentages above 90%. On the other hand, it offers a more complex analysis, as in addition to reliability, it offers the possibility of analyzing polarity according to several categories (very negative, negative, neutral, absent, positive, and very positive), instead of giving a categorical answer. Furthermore, it allows for an analysis of subjectivity (traces of opinions or objective views), agreement (the level of emotional agreement), and irony (traces or the absence of irony).

(d) Qualitative content analysis

This section corresponds to a qualitative methodology, as it involves the analysis of content by means of a semantic analysis of the text. A word cloud is a visual representation of a set of words where the size of each word is based on its frequency or importance in a text. Thus, the "nubedepalabras" application was chosen to generate frequency graphs with two essential elements: (a) elimination of duplicates and (b) elimination of empty and worthless words. In this way, the premises established by Krippendorff [56] on the treatment of discourse were taken into account.

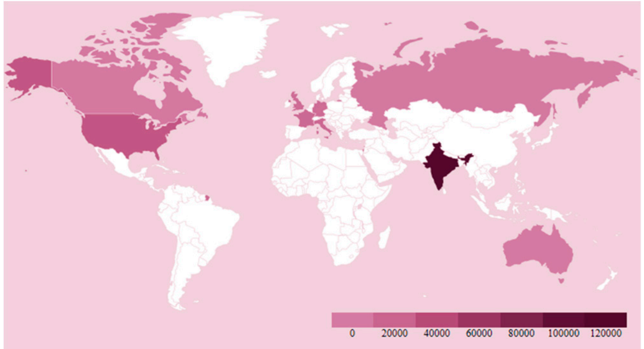
Twitter **Instagram** **Facebook**

(**a**) **Likes**



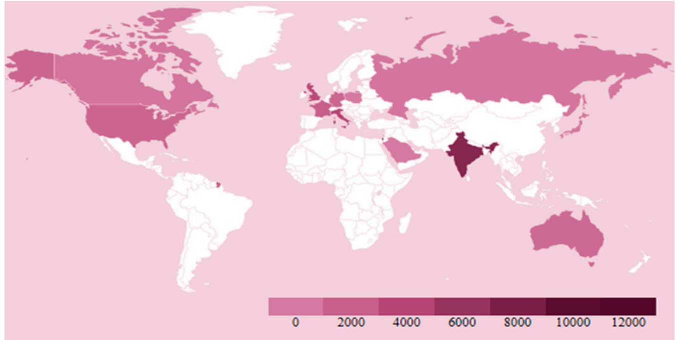
Germany (M = 26.91; DS = 50.252); Saudi Arabia (M = 640.67; DS = 964.17); Australia (M = 66.40; DS = 84.39); Canada (M = 78.29; DS = 286.18); Japan (M = 876.39; DS = 982.79); Korea (M = 105.07; DS = 296.20); Poland (M = 23.25; DS = 42.03); Russia (M = 99.48; DS = 96.21); the United States (M = 764.97; DS = 1510.68); Israel (M = 2876.48; DS = 4313.26); Italy (M = 164.19; DS = 303.88); India (M = 2737.72; DS = 3118.77); France (M = 113.54; DS = 183.99); the United Kingdom (M = 454.99; DS = 1336.13); Total (M = 344.81; DS = 1271.54)

ANOVA F = 604.567; *p* < 0.000



Germany (M = 13,153.67; SD = 6011.136); Australia (M = 3099.54; SD = 1084.321); Canada (M = 4333.73; SD = 2260.947); Russia (M = 4036.93; SD = 1886.510); the United States (M = 28,964.94; SD = 12,606.527); Israel (M = 11,629.92; SD = 4099.163); Italy (M = 16,086.45; SD = 6891.016); India (M = 107,827.60; SD = 48,074.336); France (M = 14,892.52; SD = 6972.507); the United Kingdom (M = 13,213.06; SD = 7907.131); Total (M = 30,864.32; SD = 42,238.803)

ANOVA F = 1169.305; *p* < 0.000

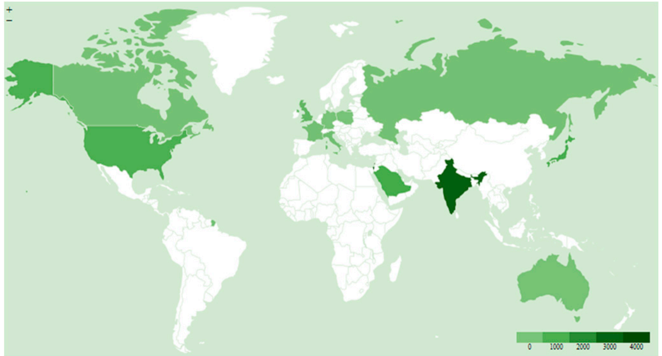


Germany (M = 1455.12; SD = 1278.135); Saudi Arabia (M = 52.05; SD = 31.406); Australia (M = 1209.11; SD = 1208.236); Canada (M = 451.11; SD = 493.358); Japan (M = 219.81; SD = 117.047); Korea (M = 120.06; SD = 115.061); Poland (M = 77.67; SD = 76.398); Russia (M = 323.41; SD = 394.563); the United States (M = 1462.09; SD = 1840.226); Israel (M = 10,414.91; SD = 11,219.808); Italy (M = 4025.93; SD = 8342.525); India (M = 7259.71; SD = 11,954.490); France (M = 2045.44; DS = 3651.447); the United Kingdom (M = 3479.65; SD = 3642.718); Total (M = 1834.01; SD = 5263.187)

ANOVA F = 206.233; *p* < 0.000

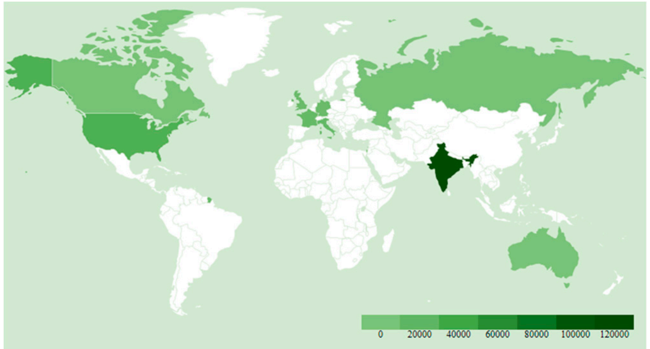
Figure 1. *Cont.*

(b) Reactions



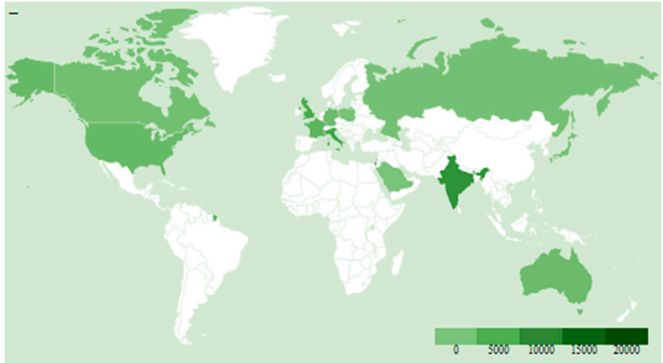
Germany (M = 31.62; SD = 59.52); Saudi Arabia (M = 1165.58; SD = 1830.73); Australia (M = 79.58; SD = 105.95); Canada (M = 101.64; SD = 361.37); Japan (M = 1051.89; SD = 1227.89); Korea (M = 170.62; SD = 493.41); Poland (M = 30.19; SD = 55.49); Russia (M = 133.50; SD = 129.93); the United States (M = 985.21; SD = 1927.86); Israel (M = 3622.96; SD = 5385.03); Italy (M = 205.69; SD = 410.65); India (M = 3148.88; SD = 3706.26); France (M = 144.64; SD = 250.58); the United Kingdom (M = 565.15; SD = 1718.92); Total (M = 423.31; SD = 1555.01)

ANOVA F = 21.507; *p* = 0.001



Germany (M = 100.92; DS = 75.167); Australia (M = 23.74; DS = 20.309); Canada (M = 48.01; DS = 54.740) Russia (M = 63.47; DS = 68.433); the United States (M = 151.79; DS = 124.3859); Israel (M = 282.29; DS = 151.876); Italy (M = 83.39; DS = 80.8279); India (M = 337.43; DS = 311.039); France (M = 137.07; DS = 203.088); the United Kingdom (M = 95.30; DS = 172.549); Total (M = 153.86; DS = 199.357)

ANOVA F = 1659.44; *p* < 0.00

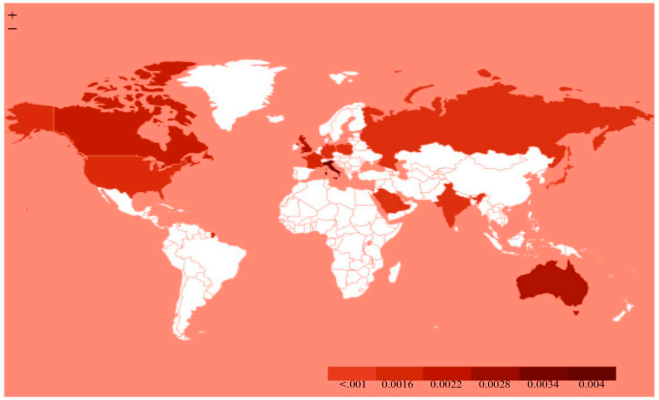


Germany (M = 1829.93; SD = 2179.512); Saudi Arabia (M = 66.68; SD = 44.209); Australia (M = 1752.39; SD = 2308.941); Canada (M = 769.50; SD = 1775.087); Japan (M = 314.48; SD = 238.106); Korea (M = 309.30; SD = 406.800); Poland (M = 112.92; SD = 132.367); Russia (M = 423.16; SD = 617.595); the United States (M = 2088.00; SD = 2610.995); Israel (M = 17,989.80; SD = 24,316.344); Italy (M = 6100.41; SD = 25,741.762); India (M = 8701.56; SD = 17,578.219); France (M = 3192.75; SD = 5402.488); the United Kingdom (M = 5339.36; SD = 8781.980); Total (M = 2639.88; SD = 9841.520)

ANOVA F = 15.37; *p* = 0.06

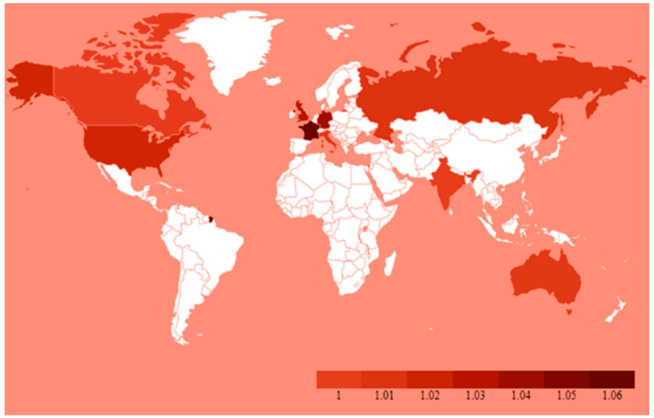
Figure 1. *Cont.*

(c) Interaction of publications



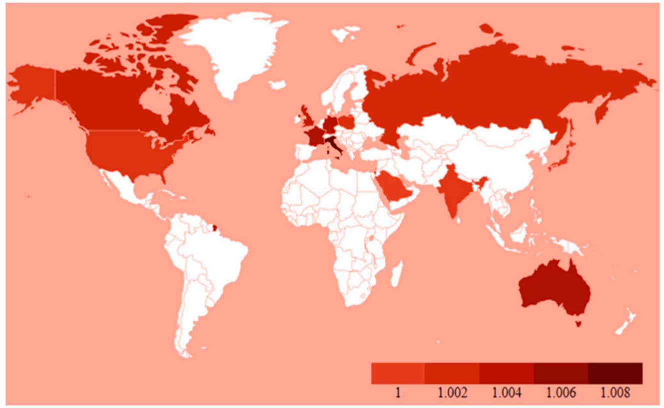
Germany (M = 0.0006; DS = 0.0008); Saudi Arabia (M = 0.0006; DS = 0.0011); Australia (M = 0.0025; DS = 0.00249); Canada (M = 0.0016; DS = 0.0039); Japan (M = 0.0000; DS = 0.0000); Korea (M = 0.0023; DS = 0.0022); Poland (M = 0.0005; DS = 0.0008); Russia (M = 0.0007; DS = 0.0006); the United States (M = 0.0008; DS = 0.0013); Israel (M = 0.0031; DS = 0.0046); Italy (M = 0.0044; DS = 0.0069); India (M = 0.0006; DS = 0.0006); France (M = 0.0011; DS = 0.0015); the United Kingdom (M = 0,0025; DS = 0,0067)

ANOVA F = 2.38; *p* < 0.000



Germany (M = 0.04; DS = 0.02); Australia (M = 0.04; DS = 0.01); Canada (M = 0.04; DS = 0.00); Russia (M = 0.04; DS = 0.01); the United States (M = 0.04; DS = 0.02); Israel (M = 0.04; DS = 0.02); Italy (M = 0.04; DS = 0.01); India (M = 0.04; DS = 0.00); France (M = 0.04; DS = 0.06); the United Kingdom (M = 0.04; DS = 0.03)

ANOVA F = 0.58; *p* < 0.001

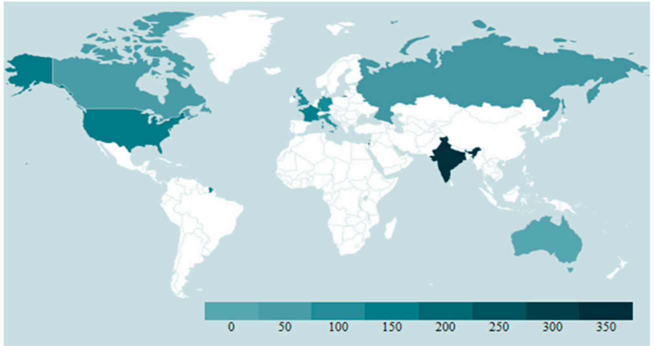


Germany (M = 0.004; DS = 0.005); Saudi Arabia (M = 0.000; DS = 0.001); Australia (M = 0.005; DS = 0.006); Canada (M = 0.003; DS = 0.006); Japan (M = 0.001; DS = 0.003); Korea (M = 0.001; DS = 0.002); Poland (M = 0.001; DS = 0.002); Russia (M = 0.002; DS = 0.003); the United States (M = 0.001; DS = 0.001); Israel (M = 0.007; DS = 0.010); Italy (M = 0.008; DS = 0.034); India (M = 0.001; DS = 0.002); France (M = 0.005; DS = 0.008); the United Kingdom (M = 0.003; DS = 0.005)

ANOVA F = 3.86; *p* < 0.001

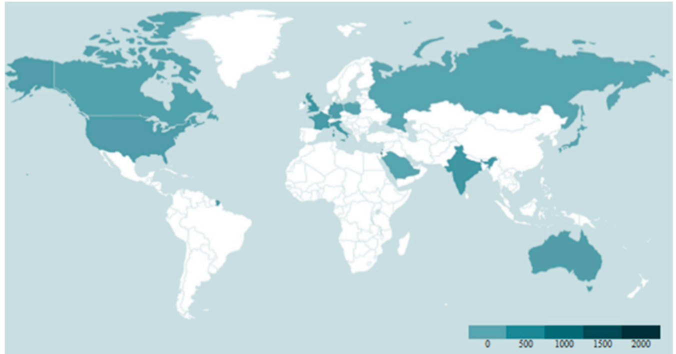
Figure 1. *Cont.*

(**d**) **Comments**



Germany (M = 100.92; SD = 75.167); Australia (M = 23.74; SD = 20.309); Canada (M = 48.01; SD = 54.740); Russia (M = 63.47; SD = 68.433); the United States (M = 151.79; SD = 124.385); Israel (M = 282.29; SD = 151.876); Italy (M = 83.39; SD = 80.827); India (M = 337.43. SD = 311.039); France (M = 137.07; SD = 203.088); the United Kingdom (M = 95.30; SD = 172.549); Total (M = 153.86; SD = 199.357)

ANOVA F = 17.31; p < 0.001

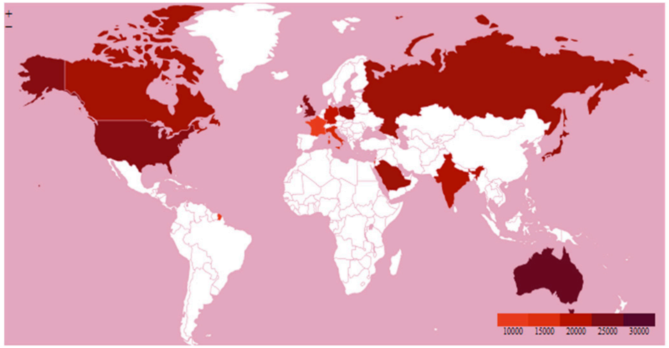


Germany (M = 111.57; SD = 200.10); Saudi Arabia (M = 7.36; SD = 11.63); Australia (M = 96.64; SD = 188.97); Canada (M = 56.71; SD = 216.699); Japan (M = 15.80; SD = 87.569); Korea (M = 44.69; SD = 117.029); Poland (M = 5.35; SD = 16.023); Russia (M = 11.91; SD = 56.734); The United States (M = 130.51; SD = 214.742); Israel (M = 1854.43; SD = 3355.149); Italy (M = 210.82; SD = 782.605); India (M = 246.41; SD = 1401.980); France (M = 175.69; SD = 330.074); the United Kingdom (M = 260.74; SD = 580.927); Total (M = 151.52; SD = 848.871)

ANOVA F = 17.69; p = 0.02

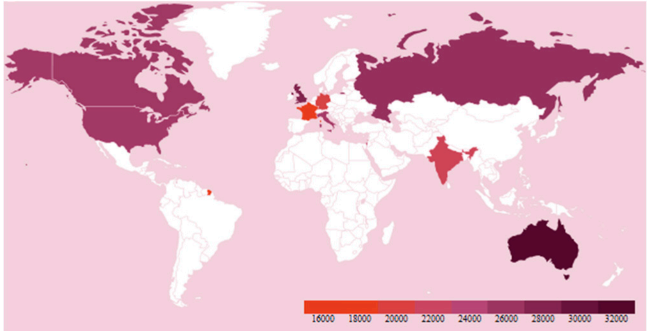
Figure 1. *Cont.*

(**e**) **Polarity**



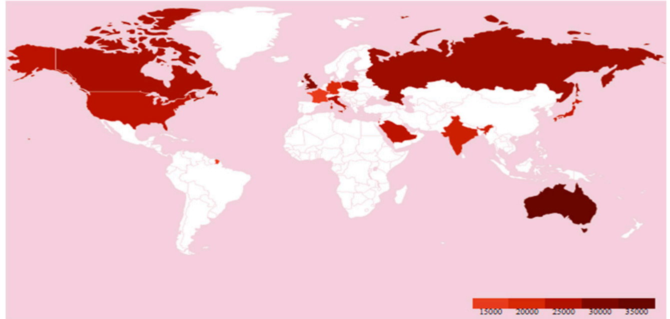
Germany (M = 18,998.14; Ds = 18,236.336); Saudi Arabia (M = 21,923.81; Ds = 18,065.956); Australia (M = 26,639.91; Ds = 17,171.401); Canada (M = 21,477.86; Ds = 18,017.983); Japan (M = 22,923.79; Ds = 18,260.238); Korea (M = 28,377.78; Ds = 17,514.006); Poland (M = 22,337.07; Ds = 18,254.613); Russia (M = 21,887.60; Ds = 18,440.971); the United States (M = 24,128.49; Ds = 17,965.977); Israel (M = 14,382.79; Ds = 17,206.693); Italy (M = 16,302.16; Ds = 17,685.032); India (M = 20,410.46; Ds = 17,385.500); France (M = 13,080.54; Ds = 16,253.691); the United Kingdom (M = 24,414.39; Ds = 17,874.566); Total (M = 20,460.56; DS = 18,222.670)

ANOVA F = 0.576 *p*= 0.691



Germany (M = 19,360.98; Ds = 18,179.293); Saudi Arabia (M = 23,911.89; Ds = 18,067.503); Australia (M = 32,022.22; Ds = 14,861.660); Canada (M = 25,832.07; Ds = 17,667.225); Japan (M = 22,614.68; Ds = 18,142.248); Korea (M = 28,108.11; Ds = 17,076.804); Poland (M = 24,186.25; Ds = 18,174.355); Russia (M = 26,899.44; Ds = 17,624.527); the United States (M = 23,947.58; Ds = 18,053.941); Israel (M = 20,653.06; Ds = 18,298.493) Italy (M = 24,699.23; Ds = 18,157.232); India (M = 21,455.71; Ds = 17,332.465); France (M = 16,324.85; Ds = 17,399.351); the United Kingdom (M = 28,906.90; Ds = 16,501.283); Total (M = 24,612.04; Ds = 17,931.039)

ANOVA F = 8.32; *p* < 0.001

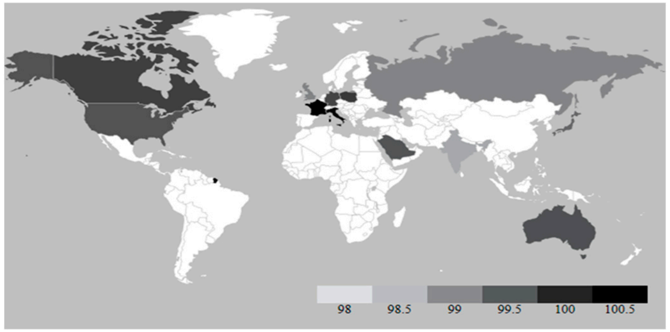


Germany (M = 19,360.98; Ds = 18,179.293); Saudi Arabia (M = 23,911.89; Ds = 18,067.503); Australia (M = 32,022.22; Ds = 14,861.660); Canada (M = 25,832.07; Ds = 17,667.225); Japan (M = 22,614.68; Ds = 18,142.248); Korea (M = 28,108.11; Ds = 17,076.804); Poland (M = 24,186.25; Ds = 18,174.355); Russia (M = 26,899.44; Ds = 17,624.527); the United States (M = 23,947.58; Ds = 18,053.941); Israel (M = 20,653.06; Ds = 18,298.493); Italy (M = 24,699.23; Ds = 18,157.232); India (M = 21,455.71; Ds = 17,332.465); France (M = 16,324.85; Ds = 17,399.351); the United Kingdom (M = 28,906.90; Ds = 16,501.283); Total (M = 24,612.04; Ds = 17,931.039)

ANOVA F = 0.16; *p* = 0.95

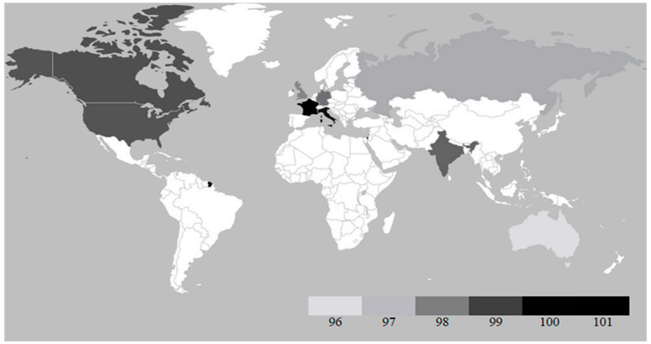
Figure 1. *Cont.*

(**f**) **Confidence**



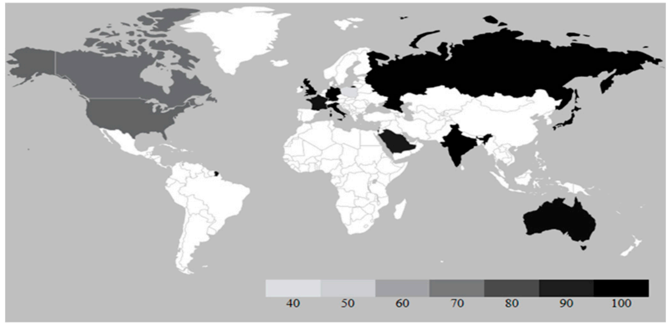
Germany (M = 98.67; Ds = 3.100); Saudi Arabia (M = 98.54; Ds = 2.906); Australia (M = 98.57; Ds = 3.022); Canada (M = 98.73; Ds = 3.123); Japan (M = 98.36; Ds = 3.617); Korea (M = 98.09; Ds = 3.884); Poland (M = 98.77; Ds = 2.885); Russia (M = 98.06; Ds = 3.893); the United States (M = 98.55; Ds = 3.071); Israel (M = 97.16; Ds = 4.264); Italy (M = 99.24; Ds = 2.604); India (M = 97.72; Ds = 3.851); France (M = 99.40; Ds = 2.039); the United Kingdom (M = 98.09; Ds = 3.618); Total (M = 98.58; Ds = 3.210)

ANOVA F = 0.545; p = 0.710



Germany (M = 97.21; Ds = 4.165); Australia (M = 95.41; Ds = 4.617); Canada (M = 97.73; Ds = 4.353); Russia (M = 96.27; Ds = 6.929); the United States (M = 97.66; Ds = 3.730); Israel (M = 98.71; Ds = 3.474); Italy (M = 98.67; Ds = 3.283); India (M = 97.43; Ds = 3.880); France (M = 99.08; Ds = 2.624); the United Kingdom (M = 96.86; Ds = 4.013); Total (M = 97.55; Ds = 4.316)

ANOVA F = 21.76; p < 0.001



Germany (M = 95.25; Ds = 14.031); Saudi Arabia (M = 89.68; Ds = 29.293); Australia (M = 92.83; Ds = 14.794); Canada (M = 71.76; Ds = 43.059); Japan (M = 95.39; Ds = 17.463); Korea (M = 83.58; Ds = 49.083); Russia (M = 95.97 Ds = 5.963); the United States (M = 73.63; Ds = 42.469); Israel (M = 96.78; Ds = 11.914); Italy (M = 96.81; Ds = 14.229); India (M = 97.23; Ds = 5.409); France (M = 91.19; Ds = 26.6119); the United Kingdom (M = 96.29; Ds = 7.322); Total (M = 84.71; Ds = 32.797)

ANOVA F = 0.30; p = 0.88

Figure 1. Heat plots and ANOVA tests on KPIs and sentiment analysis (polarity and confidence).

3.3. Study Variables

Two types of variables are addressed in this research: key performance indicators and sentiment analysis.

Key performance indicators, or KPIs, are indices that allow us to analyze the effectiveness and behavior of social network profiles (see Table 2). More specifically, a key performance indicator (KPI) is a metric used to measure the performance or progress of an organization, company, project, or process towards achieving its objectives. KPIs are important tools for evaluating and monitoring performance, as they provide quantitative and qualitative information about key aspects of an activity or business, being particularly relevant in the study of social networks.

Table 2. Definitions of key performance indicators (KPIs).

Reactions	Twitter	"Number of Retweets, quotes, replies and likes on tweets published in the selected period" [57].
	Instagram	"Number of organic likes and organic comments on posts published in the selected period" [57].
	Facebook	"Number of reactions ("I like", "I love", "I am amused", "I care", "I am amazed", "I am sad", "I am angry"), comments and shares on the "posts" published in the selected period" [57].
Likes	Twitter	"Number of "likes" of Tweets published in the selected period" [57].
	Instagram	"Number of organic "likes" on "posts" published in the selected period" [57].
	Facebook	"Number of "Likes" on the "posts" published in the selected period", apply to the kpi "I love it", "it makes me angry", "it makes me sad", "I care for you" [57].
Comments	Twitter	"Number of replies to Tweets posted in the selected period" [57].
	Instagram	"Number of organic comments on posts published during the selected period of time" [57].
	Facebook	"Number of user posts published in the selected period and to which the Page reacted (I like, I love, I am amused, I care, I am sad, I am angry)" [57].
Interaction of publications	Twitter	"Average number of reactions per tweet in a day in relation to the number of followers on the same day in the selected period. If a user with 200 followers receives a total of 30 reactions to his 10 tweets in a day, the interaction is 1.5% (30/10/200 = 0.015 = 1.5%)" [57].
	Instagram	Average number of organic likes and organic comments per post per day in relation to the number of followers on the same day during the selected time period [57].
	Facebook	"The average number of interactions per post in relation to the number of users who have seen these posts" [57].

A sentiment analysis makes it possible to determine the emotional impact of a text. The variables are presented below (see Table 3).

Table 3. Sentiment analysis variables.

Confidence	Variable determining confidence in generic sentiment analysis.
Polarity	It analyses whether the language used has emotionality or lacks it by categorising texts by values: very positive, positive, neutral, negative, very negative or no feeling" [58].
Agreement	It marks the agreement between the sentiments detected in the text. the sentence or segment to which it refers" (MeaningCloud. 2023) [58]. This is a categorical variable indicating whether there is homogeneity or agreement of emotions or diversity.
Subjectivity	Dichotomous variable that studies the connotative marks of the text, indicating whether the publication conveys an opinion (subjective) or whether it describes a fact or circumstance (objective).
Irony	Dichotomous variable that studies the existence of ironic or non-ironic marks.

3.4. Data Analysis

A series of analyses are necessary to either accept or refute the hypotheses. The software used was IBM SPSS.

Firstly, the descriptive results of each KPI and a sentiment analysis in terms of means—a measure of central tendency that represents the average value of a set of data—and standard deviation—indicates the data dispersion around the mean—should be analyzed for each nation and social network.

In order to compare both the KPI and sentiment analysis variables between nations for each social network, an Analysis of Variance (ANOVA) test was applied for scale variables (polarity) and ratio variables (KPIs). ANOVA is a statistical test used to compare the means of three or more groups and to determine if there are significant differences between them. It allows for evaluating whether the observed differences in the data are a result of variability between groups or simply due to chance. ANOVA is based on an analysis of the variance of the data to make statistical inferences.

For dichotomous variables (subjectivity, irony, and emotional agreement), a Chi-square test (χ^2) was applied, which is used to determine if there is a significant relationship between two categorical variables.

To visualize these results more effectively, heatmaps were created using Excel software. A heatmap is a visual representation that uses colors to display the distribution or variation of a variable in a data matrix or table. It is commonly used to highlight patterns, trends, or concentrations of values in a dataset. The intensity of the color in each cell of the heatmap provides a quick visualization of the magnitude or density of the values. Cells with higher values are displayed with more intense or darker colors, while cells with lower values are displayed with lighter colors.

To test the strength of the sentiment analysis in posts regarding the number of likes, a multiple regression analysis was applied, which is a statistical technique that seeks to establish a relationship between a dependent variable and two or more independent variables. It is used to predict or explain the value of a dependent variable based on independent variables.

To visualize these results more effectively, word clouds were created [45]. Word clouds are generated by algorithms that process the text and determine the frequency of each word. Based on this information, visualizations are created where the most common words are presented in a larger size and placed in random or structured positions in the image. This technique is widely used to summarize or visualize patterns in large amounts of text [59]. For example, it can be applied in user opinion analyses, surveys, blogs, articles, political speeches, among others. By looking at a word cloud, it is possible to obtain a general idea of the most important or recurring topics within a set of texts without having to read all of the contents. Word clouds are useful for highlighting trends, identifying keywords, quickly understanding the content of a text, or simply making a set of words visually appealing [60]. There are various online tools and specialized software that allow for generating customized word clouds and adjusting parameters such as shape, color, fonts, and size of the cloud. In our case, we used the "nubesdepalabras" application, following the methodological principles of Krippendorff. Duplicates and meaningless words such as prepositions and articles were eliminated. Thus, the unit of analysis was meaningful words, with the most frequent ones represented in a larger size. They were organized into two typologies of categories: (a) thematic (a.1 national identity, a.2 military jargon or terminology, and a.3 current news) and (b) type of language (b.1 technical–military, where everyday activities such as maneuvers, training, or materials are presented, and b.2 humanitarian, with information about values, civil support actions, or protection of vulnerability).

4. Results

The analysis of the means and standard deviations of the key performance indicators—likes, comments, reactions, and interaction of posts—and sentiment analysis—polarity, agreement, subjectivity, irony, and trust—determined the existence of significant differences between nations.

In this sense, we found that there are significant differences in "likes" in the three social networks (Twitter, ANOVA, F = 604.56, $p < 0.001$; Instagram, ANOVA, F = 1169.30, $p < 0.001$; Facebook, ANOVA, F = 206.233, $p < 0.001$). More specifically, India and Israel have higher averages than the rest of the nations in the three social networks, with a very active digital community that reinforces defense publications through the "reaction" of "liking" them (see Figure 1a). In addition, there are significant differences in the average number of likes received depending on the social network, with Instagram being particularly active.

More generally, the number of reactions shows significant differences in the Twitter (ANOVA, F = 21.50, $p = 0.001$) and Instagram (ANOVA, F = 1659.44, $p < 0.001$) networks between nations, in contrast to Facebook, where this cultural diversity is blurred (see Figure 1b). In this sense, Israel and India again stand out with very active communities. Again, there are differences between the social networks, with Facebook being the most active.

In terms of interaction to publications, there are again significant differences between nations on Twitter (ANOVA, F = 2.38, $p < 0.001$), Instagram (ANOVA, F = 0.58, $p < 0.001$), and Facebook (ANOVA, F = 3.86, $p < 0.001$). On Twitter, Italy, Israel, and Canada stand out, while India shows a very low interaction (see Figure 1c). Finally, it is worth noting that Instagram is the best positioned.

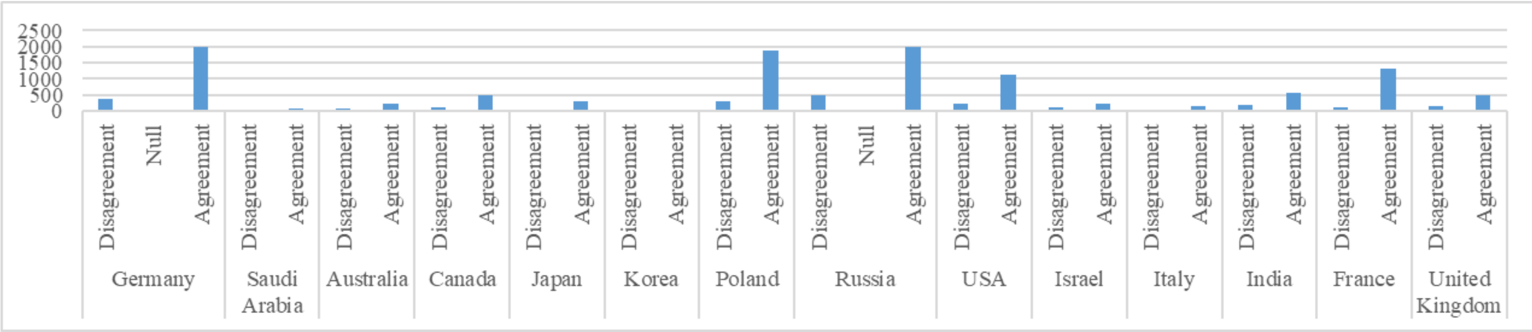
In the case of comments, the same pattern of cultural diversity is found, as there are significant differences especially on Twitter (ANOVA, F = 17.31, $p < 0.001$, where India stands out again, followed by Israel and the USA. Similarly, in Facebook (ANOVA, F = 17.69, $p = 0.02$), significant differences were found, although with a lower percentage of confidence. In fact, in the heat graph, there are hardly any significant differences (see Figure 1d).

In terms of polarity, there is significant diversity on Instagram (ANOVA, F = 8.32, $p < 0.001$), while on Twitter and Facebook, there are no significant differences in the emotionality of the publications between nations (see Figure 1e). In this sense, on Instagram, we found that posts from central and southern Europe have a lower polarity than those from Anglo-Saxon countries. Thus, it is the French army which has the lowest polarity in its publications and the Australian army which, together with the United Kingdom and Canada, are the nations with the highest polarities. It should also be noted that polarity tends to be low or negative on Twitter, very positive on Facebook, and oscillating between negative or very negative and very positive on Instagram, depending on the nation.

On the other hand, in the case of the dichotomous variables, we found significant differences between social networks. In the case of Twitter, there are no differences between nations in agreement (Xi2 = 3.65. $p = 0.45$), subjectivity (Xi2 = 7.77. $p = 0.53$), and irony (Xi2 = 6.38. $p = 1$) (see Figure 2). In the case of Instagram, there are significant differences in agreement (Xi2 = 173.80. $p < 0.001$), subjectivity (Xi2 = 104.08. $p < 0.001$), and irony (Xi2 = 25.01. $p = 0.02$) (see Figure 2). Finally, it is worth noting the absence of significant differences on Facebook in agreement (Xi2 = 3.42. $p = 0.63$), subjectivity (Xi2 = 11.33. $p = 0.33$), and irony (Xi2 = 3.49. $p = 0.66$) (see Figure 2). However, it is worth noting that the majority of publications (although in different proportions) are objective, with emotional agreement or concordance and no irony. However, these variables play a transcendental role in some nations to achieve a greater number of likes.

Equally relevant is the trust index attributed to the sentiment analysis in global terms (see Figure 1f). In all cases, the average scores exceed 90%, giving a very high level of trust in all nations and in each of the social networks. This indicator allows us to confirm that the analysis of polarity, agreement, subjectivity, and irony was carried out adequately.

Agreement Twitter



Instagram

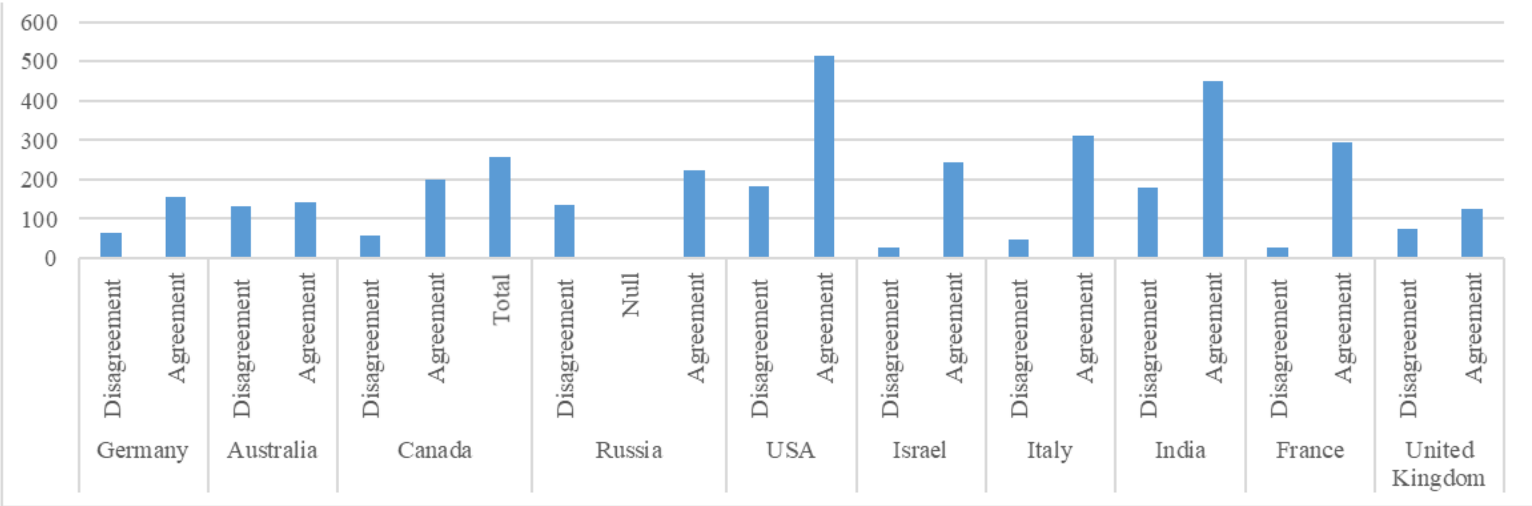
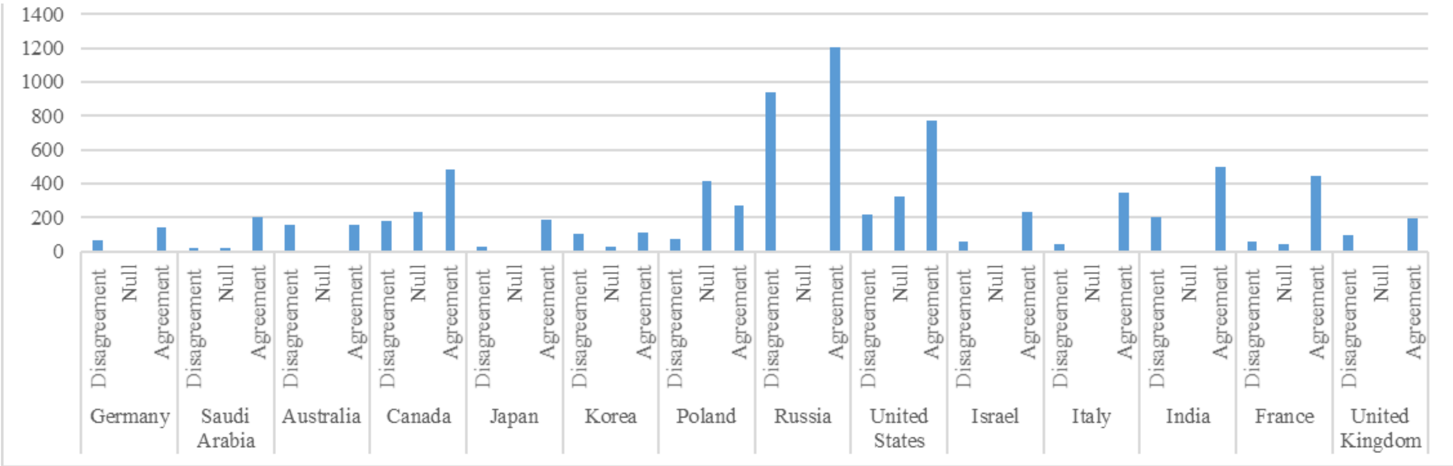


Figure 2. *Cont.*

Facebook



Subjectivity Twitter

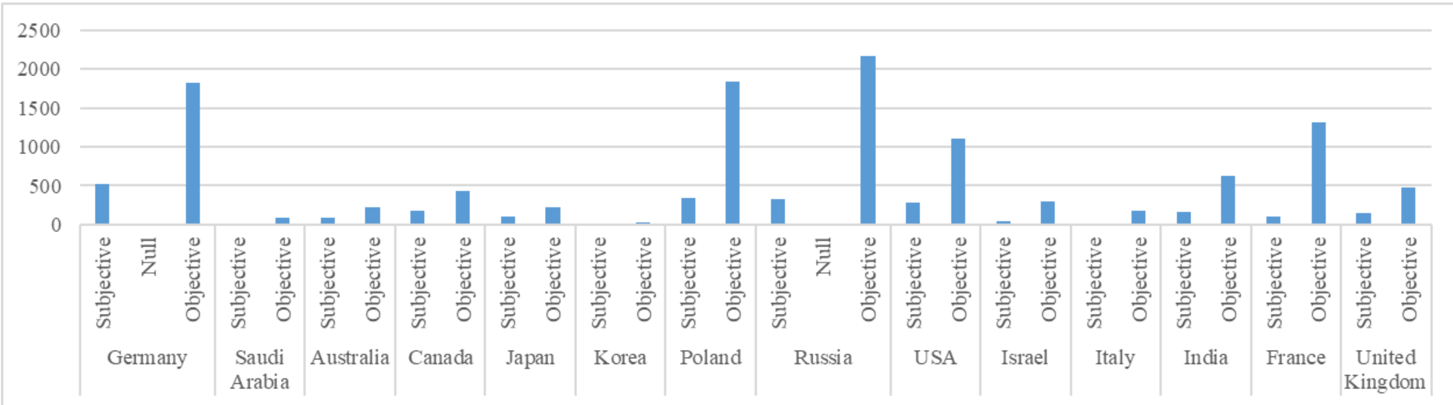
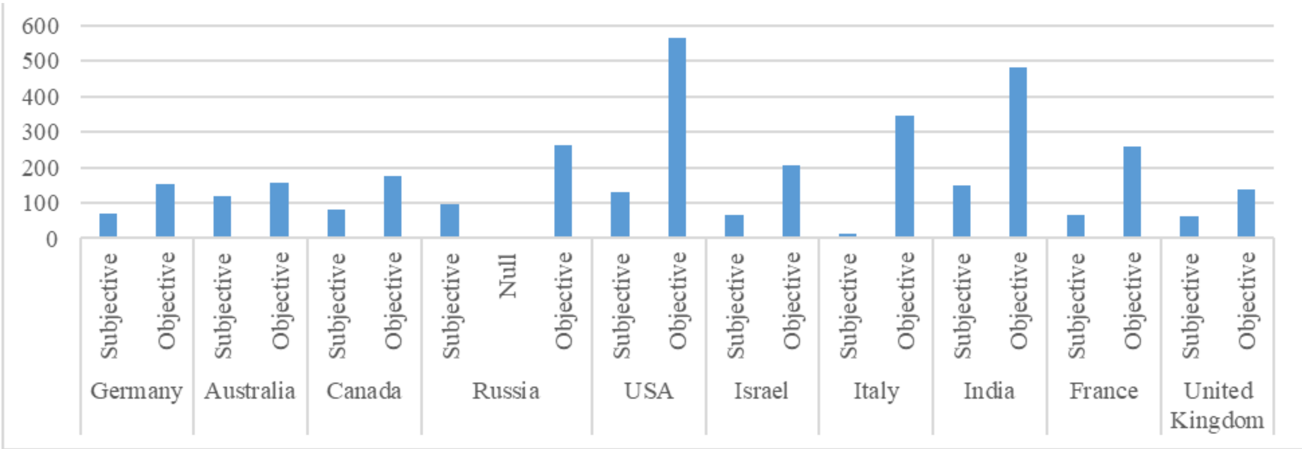


Figure 2. *Cont.*

Instagram



Facebook

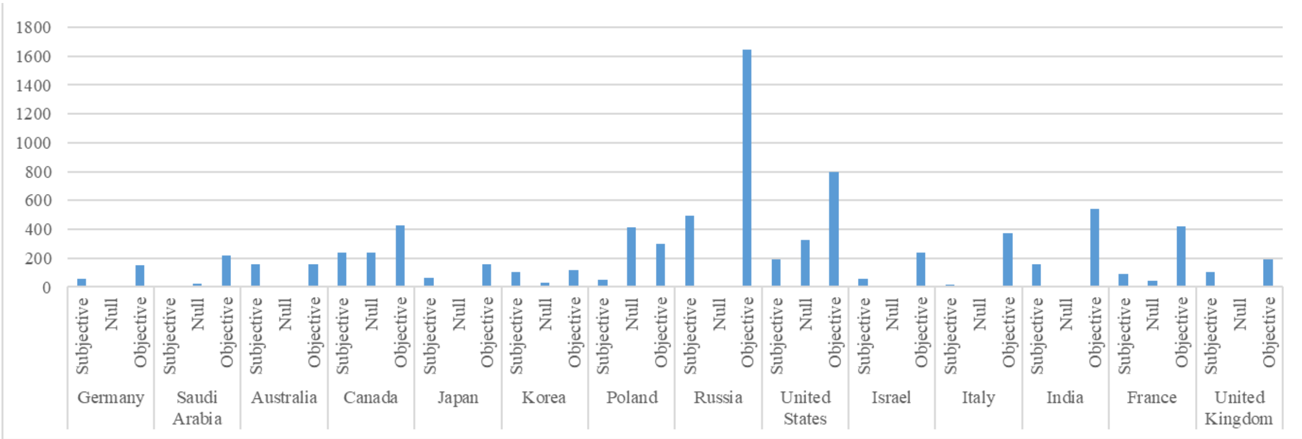
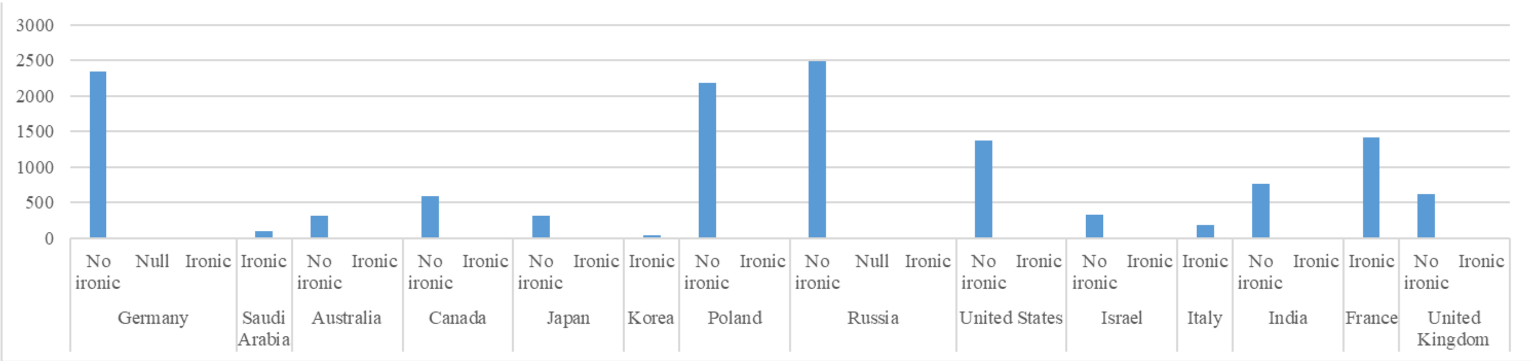


Figure 2. *Cont.*

Irony Twitter



Instagram

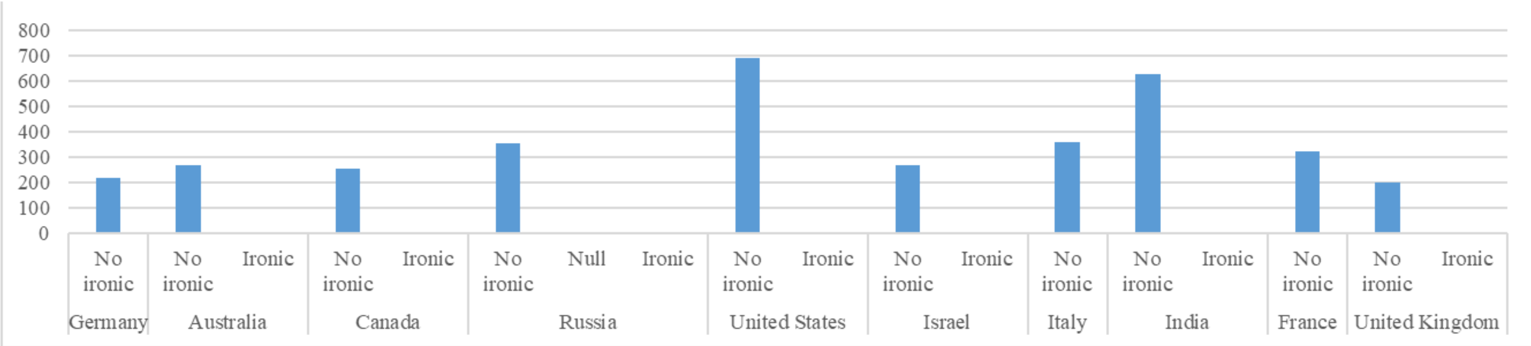


Figure 2. *Cont.*

Facebook

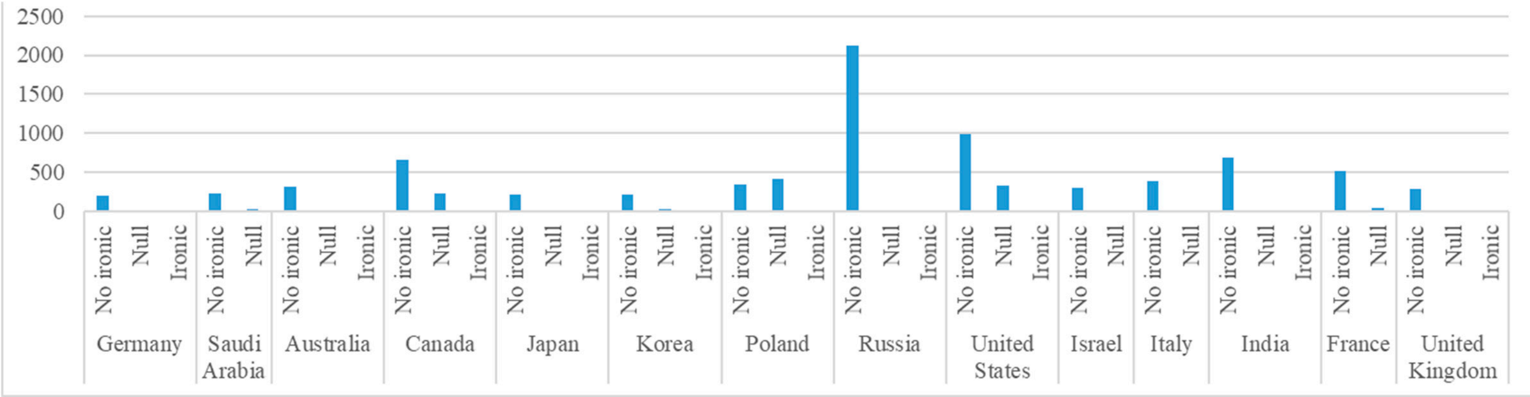


Figure 2. Sentiment analysis graphs (subjectivity, agreement, and irony).

In summary, hypothesis 1 is partially confirmed, as there are significant differences in the key performance indicators ("likes" for Twitter, Instagram, and Facebook; reactions for Twitter and Instagram; productivity for Twitter, Instagram, and Facebook; and comments for Instagram and Facebook) and sentiment analysis between nations (polarity for Instagram and confidence for Instagram; agreement for Instagram; subjectivity for Instagram; and irony for Instagram). Similarly, hypothesis 2 is confirmed, as the Twitter, Instagram, and Facebook social networks behave differently in terms of key performance indicators (KPIs) and sentiment analysis.

According to scientific evidence, there is an important relationship between positive polarity and the number of likes. Thus, the greater the polarity, understood as publications with positive sentiments, the more likes they will receive and the better their web positioning. For this reason, a multiple regression model was carried out for each nation and social network to confirm this hypothesis.

In this sense, a sentiment analysis only plays an essential role in a series of nations (see Table 4) and only for the social networks Twitter and Facebook:

- Saudi Arabia: The role of a sentiment analysis is decisive for the number of "likes" as the value of agreement (t = -3.5, $p < 0.001$) indicates an indirect relationship on Twitter. Thus, the greater the emotional diversity, the higher the number of likes. However, it should be noted that the ratio of objective/subjective publications has a ratio of 5.91/1, so that despite the fact that subjective publications are less frequent, they have a greater impact on the population (see Figure 2).
- Australia: For Twitter, the polarity value (t = 2.34, $p < 0.002$) shows that the greater the polarity, the more likes it receives, and the agreement value (t = -1.95, $p < 0.05$) indicates that the greater the diversity, the greater the number of likes. In this sense, it should be noted that the objectivity/subjectivity ratio is 3.98/1, while in other countries, such as France, the ratio is 11.58 (see Figure 2). In the Facebook network, the polarity (t = 2.28, $p = 0.02$) maintains the same positive relationship.
- Japan: On Twitter, the polarity values (t = 3.14, $p < 0.001$) show a positive relationship.
- Korea: On Facebook, the polarity values (t = 2.77, $p < 0.001$) present a positive relationship, as does subjectivity (t = 2.16, $p = 0.03$), showing that objective publications have a greater number of likes. In this sense, it is necessary to indicate that the ratio between objective/subjective publications is 1.07/1, in favor of objectivity (see Figure 2).
- Poland: On Twitter, it has negative polarity values (t = -2.21, $p = 0.03$), with publications that have a higher negative polarity, i.e., those showing cases of death, accidents, or similar, enjoying a greater number of likes.
- Russia: In the case of Facebook, it has negative polarity values (t = -3.96, $p < 0.001$), with a higher number of likes obtained on posts.
- The USA: On the Twitter network, it presents subjectivity values (t = 2.27, $p = 0.02$), i.e., posts with an objective load achieve a greater number of likes. In this sense, it is necessary to indicate how the publications are mostly positive, with a ratio of 4.05 compared with subjective "posts" (see Figure 2). In the case of Facebook, the polarity values (t = 3.39, $p < 0.001$) show a positive relationship, in such a way that the greater the amount of positive feelings, the more likes the community grants.
- France: In the case of Twitter, it presents polarity values (t = 2.65, $p = 0.01$) with a positive relationship, as does agreement (t = 1.29, $p < 0.02$), i.e., posts with positive polarity and emotional agreement have a higher number of likes. It should be noted that objective posts have a ratio of 11.58/1 compared with subjective posts and are therefore much more frequent (see Figure 2).

Table 4. Multiple regressions for the number of likes.

		Twitter			Instagram			Facebook		
Country	**Indicators**	**t**	***p***	**R^2**	**t**	***p***	**R^2**	**t**	***p***	**R^2**
Germany	Constant	0.64	0.53	0.99	32.456	<0.001	>0.99	4.63	<0.001	0.92
	Comments				<−0.001	<0.001		−0.12	<0.001	
	Reactions	25.83	<0.001		<0.001	<0.001				
	Interaction of publications	−6.55	<0.001		0.153	0.878		32.77	<0.001	
	Polarity	0.69	0.49		<0.001	0.42		0.14	0.89	
	Agreement	0.44	0.66		0.263	0.793		−0.62	0.54	
	Subjectivity	−0.68	0.5		0.783	0.435		−0.24	0.81	
	Irony	0.78	0.44					−0.21	0.83	
	Confidence	0.2	0.84		−0.602	0.548		−1.87	0.06	
Saudi Arabia	Constant	−4.12	<0.001	0.99				0.85	0.39	0.98
	Comments							−20.95	<0.001	
	Reactions	99.07	<0.001					95.42	<0.001	
	Interaction of publications	5.7	<0.001					2.20	0.03	
	Polarity	0.25	0.80					0.88	0.38	
	Agreement	−3.5	<0.001					−1.49	0.14	
	Subjectivity	2.21	0.03					0.71	0.48	
	Irony							1.79	0.08	
	Confidence	4.08	<0.001					1.80	0.07	
Australia	Constant	−1.45	0.15	0.99	0	1	>0.90	1.38	0.17	0.87
	Comments				−7,876,135.2	0		−0.40	<0.001	
	Reactions	9.55	<0.001		404,950,108	0		−3.67	<0.001	
	Interaction of publications	−0.26	0.79		0	1		4.67	<0.001	
	Polarity	2.34	0.02		0	1		2.28	0.02	
	Agreement	−1.95	0.05		0	1		−1.34	0.18	
	Subjectivity	−0.87	0.39		0	1		0.80	0.42	
	Irony	0.49	0.63		0	1		0.36	0.72	
	Confidence	1.7	0.09		0	1		0.48	0.63	
Canada	Constant	−1.27	0.20	0.99	0	1	>0.90	9.64	<0.001	0.51
	Comments				−16,521,242.6	0		−6.55	<0.001	
	Reactions	70.42	<0.001		695,316,416	0		11.19	<0.001	
	Interaction of publications	11.87	<0.001		0	1		−10.51	<0.001	
	Polarity	1.52	0.13		0	1		3.45	<0.001	
	Agreement	0.36	0.72		0	1		−0.51	0.61	
	Subjectivity	−0.55	0.58		0	1		1.26	0.21	
	Irony	−0.82	0.41		0	1		0.33	0.74	
	Confidence	0.95	0.34		0	1		0.87	0.39	
Japan	Constant	−1.06	0.29	0.98				2.95	<0.001	0.78
	Comments							−9.65	<0.001	
	Reactions	113.31	<0.001					22.78	<0.001	
	Interaction of publications							8.44	<0.001	
	Polarity	3.14	<0.001					0.53	0.59	
	Agreement	−0.82	0.41					−0.70	0.48	
	Subjectivity	−1	0.32					0.27	0.78	
	Irony	0.66	0.51					0.66	0.50	
	Confidence	1.2	0.23					1.17	0.26	

Table 4. *Cont.*

		Twitter			Instagram			Facebook		
Country	**Indicators**	**t**	***p***	**R^2**	**t**	***p***	**R^2**	**t**	***p***	**R^2**
Korea	Constant	−0.11	0.92	0.95				13.53	<0.001	0.90
	Comments							1.00	0.32	
	Reactions	21.69	<0.001					3.34	<0.001	
	Interaction of publications	−0.81	0.42					−0.30	0.76	
	Polarity	−0.43	0.67					2.77	0.01	
	Agreement	0.93	0.36					−0.40	0.69	
	Subjectivity	−0.97	0.34					2.16	0.03	
	Irony							−0.33	0.74	
	Confidence	0.12	0.90					−1.28	0.20	
Poland	Constant	1.03	0.30	0.99				0.45	0.65	0.97
	Comments							−43.00	<0.001	
	Reactions	62.05	<0.001					25.66	<0.001	
	Interaction of publications	−16.23	<0.001					−18.42	<0.001	
	Polarity	−2.21	0.03					−46.00	0.65	
	Agreement	0.13	0.90					0.84	0.40	
	Subjectivity	1.45	0.15					0.84	0.40	
	Irony	0.07	0.95					1.03	0.30	
	Confidence	−0.88	0.38					0.60	0.55	
Russia	Constant	1.31	0.19	0.99	0	1		5.85	<0.001	0.91
	Comments				−14,565,702.1	0		−16.86	<0.001	
	Reactions	22.84	<0.001		44,230,202	0		14.65	<0.001	
	Interaction of publications	−11.07	<0.001		0	1		−11.29	<0.001	
	Polarity	1.07	0.30		0	1		−3.96	<0.001	
	Agreement	−0.22	0.82		0	1		−0.46	0.64	
	Subjectivity	1.89	0.06		0	1		0.85	0.40	
	Irony	1.07	0.28		0	1		0.37	0.71	
	Confidence	−0.7	0.48		0	1		0.49	0.63	
E.E.U.U.	Constant	0.55	0.58	1	0	1	>0.90	5.10	<0.001	0.95
	Comments				−4,260,484.45	0		−2.87	<0.001	
	Reactions	28.23	<0.001		84,892,913	0		12.40	<0.001	
	Interaction of publications	−5.51	<0.001		0	1		−11.56	<0.001	
	Polarity	−0.7	0.48		0	1		3.39	<0.001	
	Agreement	1.44	0.15		0	1		0.43	0.67	
	Subjectivity	2.27	0.02		0	1		0.11	0.91	
	Irony	0.65	0.52		0	1		0.08	0.93	
	Confidence	−0.53	0.60		0	1		−0.71	0.48	
Israel	Constant	0.42	0.68	1	0	1	>0.90	3.85	<0.001	0.98
	Comments				−69,246,099.4	0		2.40	0.02	
	Reactions	2.01	0.05		136,596,874	0				
	Interaction of publications	3.67	<0.001		0	1		33.65	<0.001	
	Polarity	1.83	0.07		0	1		0.27	0.79	
	Agreement	−0.84	0.40		0	1		−0.30	0.77	
	Subjectivity	0.73	0.47		0	1		−1.01	0.31	
	Irony	0.01	0.99		0	1		−1.42	0.16	
	Confidence	−0.44	0.66		0	1		−1.23	0.22	

Table 4. *Cont.*

		Twitter			Instagram			Facebook		
Country	**Indicators**	**t**	***p***	**R^2**	**t**	***p***	**R^2**	**t**	***p***	**R^2**
Italy	Constant	2.7	0.01	1	0	1	>0.90	−0.09	0.93	1.00
	Comments				−15,339,667.6	0		−57.96	<0.001	
	Reactions	19.89	<0.001		1,305,776,430.92	0		18.14	<0.001	
	Interaction of publications	−6.09	<0.001		0	1		−0.30	0.76	
	Polarity	1.35	0.18		0	1		1.83	0.07	
	Agreement	1.55	0.12		0	1		0.75	0.46	
	Subjectivity	−1.48	0.14		0	1		−0.77	0.44	
	Irony				0	1		0.27	0.79	
	Confidence	−2.44	0.02		0	1		0.18	0.86	
India	Constant	0.32	0.75	1	0	1	>0.90	.40	0.68	0.99
	Comments				−8,417,823.6	0		−58.05	<0.001	
	Reactions	16.46	<0.001		1,247,521,905.64721	0		18.16	<0.001	
	Interaction of publications	−3.62	<0.001		0	1		-.30	0.76	
	Polarity	1.26	0.21		0	1		1.83	0.06	
	Agreement	1.28	0.20		0	1		1.05	0.29	
	Subjectivity	0.26	0.79		0	1		−0.79	0.43	
	Irony	0.04	0.97		0	1				
	Confidence	0.08	0.93		0	1				
France	Constant	−0.39	0.70	0.99	0.00	1.00	>0.90	1.56	0.12	0.90
	Comments	−22.31	<0.001		−7,802,809.848	0.00		−26.35	0.05	
	Reactions	11.78	<0.001		35,336,453.9256664	0.00				
	Interaction of publications	0.37	0.71		<0.001	1.00		60.64	<0.001	
	Polarity	2.65	0.01		<0.001	1.00		1.74	0.08	
	Agreement	1.29	0.20		<0.001	1.00		−0.37	0.71	
	Subjectivity	−1.02	0.31		<0.001	1.00		−1.82	0.07	
	Irony							1.70	0.09	
	Confidence	0.71	0.48		<0.001	1.00		1.70	0.09	
UK	Constant	−0.57	0.57	1	32.456	<0.001	>0.90	0.02	0.99	0.47
	Comments	2.34	0.02		-2.39×10^{17}	<0.001		−18.99	<0.001	
	Reactions	9.49	<0.001		3.72×10^{18}	<0.001		32.80	<0.001	
	Interaction of publications	0.45	0.66		0.153	0.878				
	Polarity	0.76	0.45		−0.808	0.420		0.91	0.37	
	Agreement	0.7	0.48		0.263	0.793		−0.50	0.62	
	Subjectivity	−0.57	0.57		0.783	0.435		1.60	0.11	
	Irony	0.22	.83					0.02	0.98	
	Confidence	0.67	0.5		−0.602	0.548		0.81	0.42	

Thus, three groups of countries with similar behavior emerged. Firstly, Japan, Korea, France, and the USA have the highest number of likes on advocacy posts that are based on positive emotions, with objective language, emotional agreement, and objectivity. In second place are Russia and Poland, whose posts with more negative sentiments have a higher number of likes, i.e., posts with deaths, natural disasters, dramatic situations with refugees, etc., have a higher number of likes. In other words, the community reacts to the actions of their armies in adverse situations to a greater extent than to pleasant or more pop-culture situations. In third place are the countries Australia and Saudi Arabia, whose digital communities give more likes to positive posts with a high emotional diversity (drama in writing), with this being the most common behavior on social media profiles.

Hypothesis 3 is thus partially confirmed, showing that there are important differences in the communicative and organizational culture of nations in defense matters.

According to the principles of qualitative treatment of content, there are two determining variables: (a) the subjects of the publications, with the most frequent being a.1 national identity, a.2 military slang or terminology, and a.3 current news, and (b) type of language, with the most frequent being b.1 technical, typical of the military world, i.e., where daily activities such as maneuvers, training, or materials are presented, or b.2 humanitarian, in other words, making greater reference to values, civilian support actions, or protection of vulnerability (see Figure 3).

In this way, we find the following:

- Russia: Themes related to its national identity are present, with words such as “russian” and “army russia” being the most frequent. At a low rate, they use terminology such as “training”, “competitions”, “forces”, and “military”, although the term “defense” is the most frequent. Finally, it should be noted how they present words referring to current situations such as “reconciliation”, “arab”, “Syrian”, and “children”. Similarly, there is a combination of technical terminology typical of the Castilian world, such as “defense”, “forces”, and “training”, as opposed to more humanitarian words such as “refugees”, “children”, and “Syrian”. There is a notable absence of terms related to the COVID-19 pandemic.
- Poland: There is a greater diversity of terms, with no major differences in frequency. Its national identity is present, as the words “polish” and “national” have a high frequency, although they do not stand out in the cloud. On the other hand, the use of the future “will”, “defense”, “army”, and “soldiers” is notable. Terms that refer to current affairs appear, such as “coronavirus”, but only in the case of Facebook and without standing out to any great extent. Their terminology is more related to technical elements, and there is a notable absence of humanistic terms.
- Germany: The most striking aspect is the number of times the German term “Bundeswehr” appears in a hashtag format in which it is joined by terms such as “team”, followed by the term “can”. In this way, national identity is constantly reinforced. There are also other terms that refer to the military world, such as “soldier”, “defense”, and “training”, as well as topical words such as “crown”.
- France: There is little national identity, as there are hardly any terms that refer directly to the nation and its army, with the exception of the term “armedeterre” in hashtag format, which is the translation of “ejército de tierra” (land army). Military slang terminology such as “regiment”, “soldier”, “operation”, “support”, and “mission” stands out, but its most frequent words are related to everyday activities. Consequently, their technical language stands out. However, they are not devoid of topical terminology, as they refer to the “COVID-19” pandemic and use some indicative support words such as “support” and “mission” directly related to international operations aimed at supporting the civilian population.
- Italy: It is striking to note the strong national identity they display through words with a high frequency such as “Italy”; “italian”; and “esercitoitaliano”, which in English means Italian army, and hashtags such as “alserviziodelpaese”, in hashtag format, which means “in the service of the nation”, and “moretogether”, which refers directly to the support of the Italian civilian population. There is a notable absence of military jargon. Similarly, there are terms related to current affairs such as “covid19”. In short, the vision is clear: to support the Italian citizenry.
- The United Kingdom: National identity appears faintly through words such as “British army” and “royal”. It is striking to note the amount of slang used in everyday activities such as “soldier”, “training”, “regiment”, “exercice”, “battalion”, and “support”. There is very little humanitarian terminology, with publications clearly using highly technical language from the world of the military. Likewise, the term “coronavirus” appears with a medium frequency, referring to current affairs.
- Australia: National identity, and group and institutional reinforcement are emphasized through the use of the hashtag “ourpeople”. Likewise, “australianarmy” appears frequently, reaffirming itself as an organization. The absence of military jargon stands

out, as opposed to more humanitarian language and references to civilian support and current affairs, such as “support”, “readynow”, “ourpreparedness”, “goodsoldiering”, “working”, “menbers”, and “families”. In this way, they present a clearly humanitarian vision of support for the civilian world while reinforcing their group identity.

- Canada: Again, corporate and national identity are reinforced through terms such as “caf”, “canadian”, “Canada”, “members”, and “royalcannavy”. All of them have a very high frequency rate. Similarly, the term “COVID-19” appears, referring to the current situation.
- USA: Corporate and national identity plays an essential role in the publications, as terms such as “Usa army”, “US”, “army”, and “airman” appear with a very high frequency rate, together with military terms such as “soldier”, “training”, “base”, “squadron”, “sgt” or sergeant, and “corps”, with high or medium frequencies. It is worth noting that the term “COVID-19” has a very high frequency on the Facebook network.
- Israel: Once again, national identity takes center stage through the acronym “idf”, israel defense forces. However, it is worth noting the appearance of terms that make a clear reference to the war conflicts in which it is involved, such as “Gaza”, an area of high tension; declared enemies of Israel such as “Hamas”; and terms such as “terror”, “Fired”, “combat”, “rocked”, and “explosive”, which refer to combat and direct confrontation.
- Saudi Arabia: The absence of reinforcement of national or corporate identity stands out, and they present an image based on the reaction to the COVID-19 pandemic, with the terms “crown”, “COVID-19”, “responsible”, “caution”, and “prevention” being relevant.
- India: National identity appears with medium frequency, with words such as “nation first” and “Indian army”. In addition, there are terms indicating unity such as “courage”, “aguardaded”, and “enemy”. The term “COVID-19” also appears. The homogeneity of the frequency of the terms is noteworthy, and it is difficult to highlight specific aspects.
- Japan: Its national identity stands out, as “Japan” has a central and hegemonic position, together with terms of unity such as “self-defense”, and slang from the military world such as “air”, “commander”, “forces”, and “base”. In addition, their good relationship with the US stands out, as they appear very frequently. They deal with the COVID-19 pandemic, but in a very mild way.
- Korea: The national identity is reinforced and clearly presented by the acronym USFK “United States Forces Korea”, with the term “republic”, “community” for group reinforcement, and more general terms such as “positive”. Likewise, the city of Daegu is largely named. They emphasize their good relationship with the USA, as “US” appears regularly and frequently. They also mention COVID-19, especially on Twitter.

In this way, we found that most nations reference COVID-19, with the exception of Israel and Russia. Other nations such as Italy, Australia, and Saudi Arabia focus heavily on humanitarian support for their civilian populations. We found, however, that countries in situations of pandemic danger, such as Japan and Korea, are close to each other in seeking cooperation and generating synergies, and feel close to each other. In contrast, other nations reinforce their national identity, such as Israel, Italy, Korea, and Japan (although they name the USA), while others reinforce the corporate identity of their armies, such as Poland, Germany, Australia, Canada, the USA, and India, and others barely name themselves, such as France, the UK, and Saudi Arabia. Finally, the use of the future “will” as a possible window to change is very relevant in Poland, Japan, and Russia.

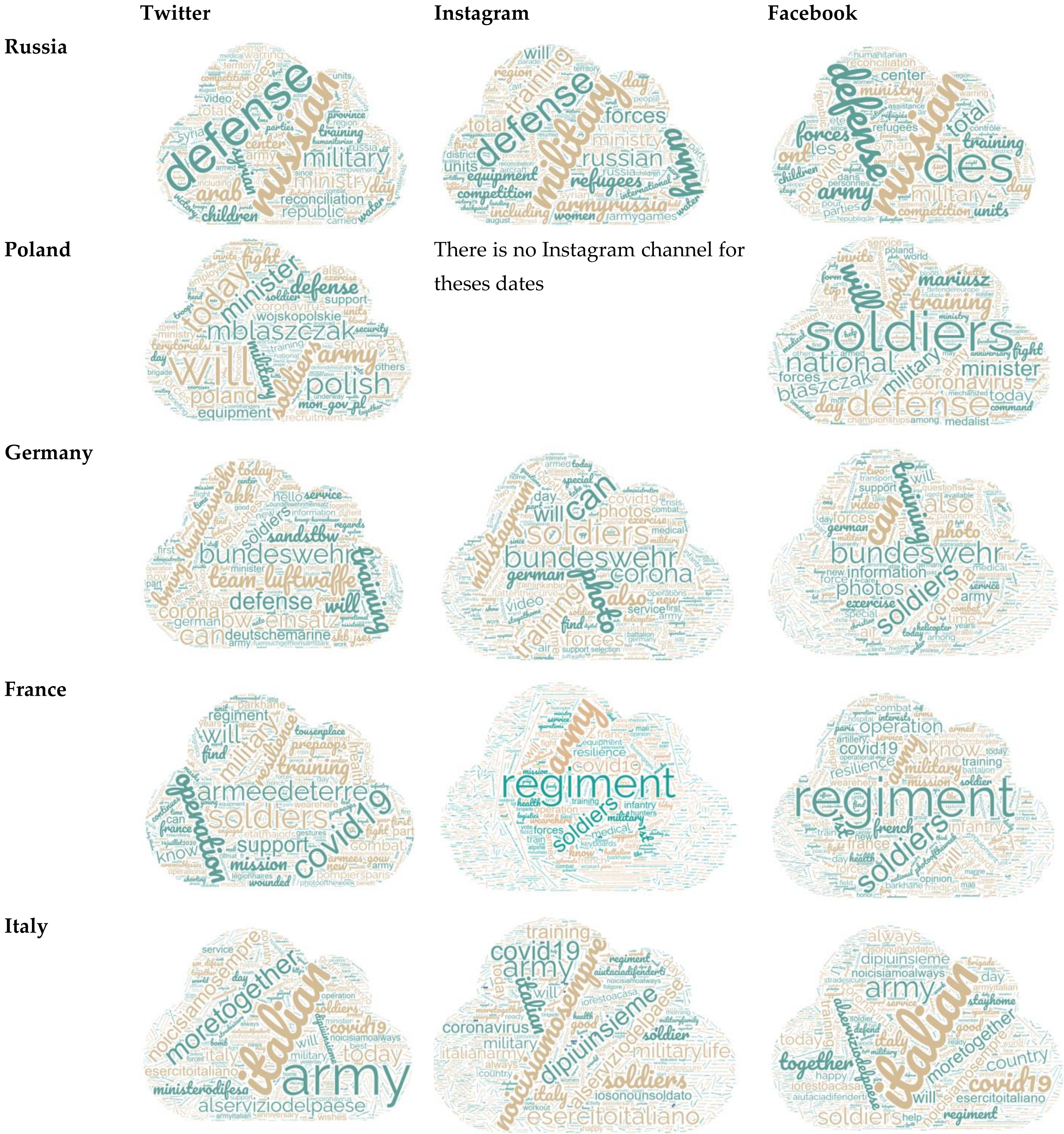


Figure 3. *Cont.*

UK

Australia

Canada

USA

Israel

Figure 3. *Cont.*

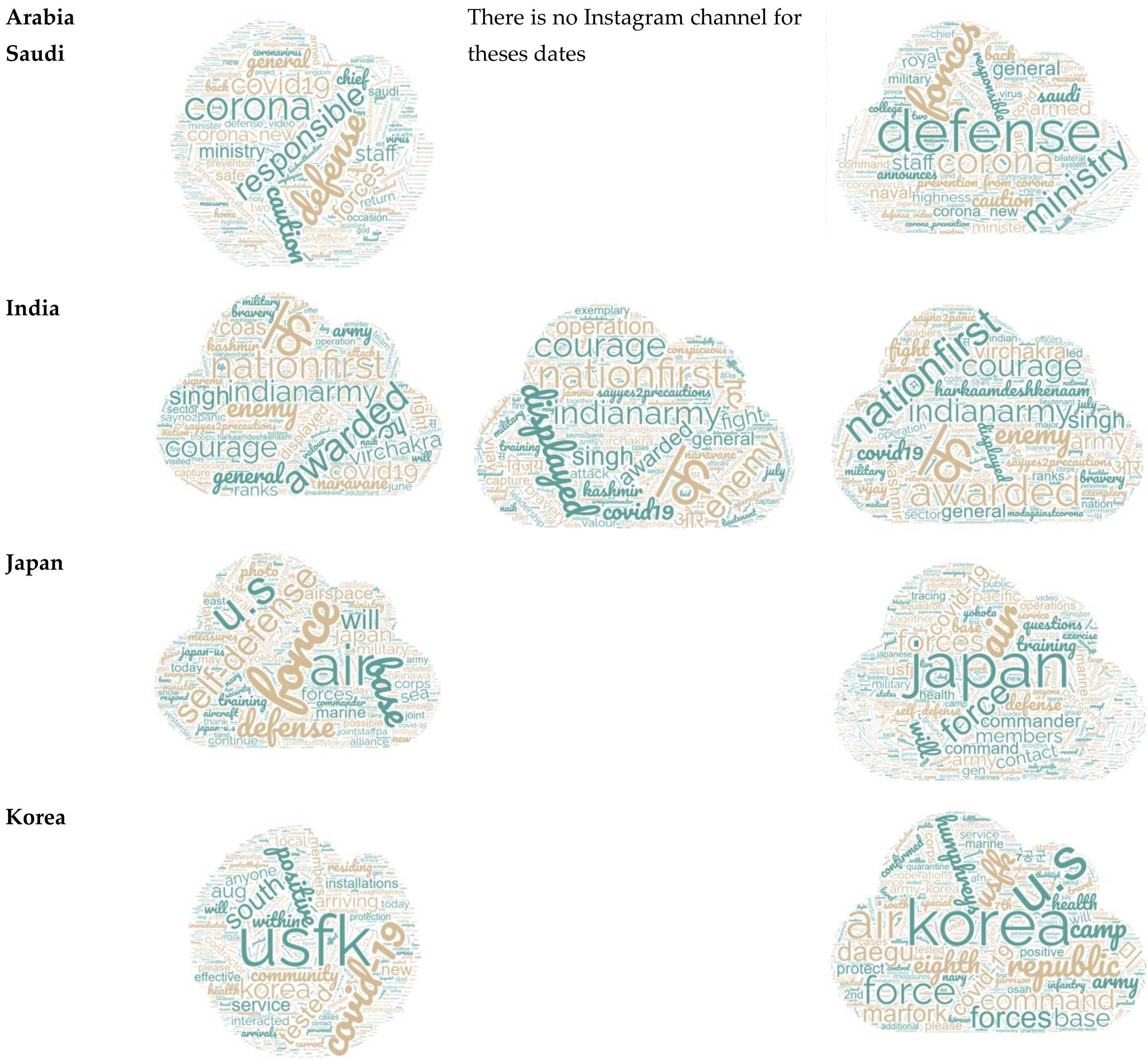


Figure 3. Word clouds for nations and social networks.

5. Discussion

Despite the widespread use of social media and its common context during the first wave of the COVID-19 pandemic, there are significant differences in terms of KPIs such as likes, reactions, comments, post interactions, and productivity across nations and social media platforms [50,51]. This necessitates a discussion of the differences between social media platforms and nations, despite the common historical moment characterized by a strong global impact and a common invisible enemy [2].

5.1. Differences between Social Media Platforms: Twitter, Instagram, and Facebook

The most influential and long-standing social media platforms are Twitter, Instagram, and Facebook [14,46,47]. While all of these platforms involve dynamic interaction between users and profiles through KPIs such as likes and comments [50,51], research conducted within the same historical context indicates differential behaviors, suggesting variations in the human needs they fulfill [46]. Other studies also highlight the ability of social networks as a thermometer of society, showcasing their influence and leadership in social processes [61].

The results show that the number of likes and post interactions is higher on Instagram, while Facebook stands out in terms of total reactions, and the total number of comments is not significantly different between Instagram and Facebook. This suggests that the digital communities using these platforms may not completely overlap, as previous research has identified generational differences [14,46,47]).

Similarly, there is homogeneity in terms of overall polarity, trust, agreement (mostly emotional agreement), subjectivity (mostly objective), and irony (mostly non-ironic) across the social media platforms. This aligns with previous studies indicating that the majority of posts on social media are positive in nature [41]. However, there are differences in terms of subjectivity and agreement. Defense profiles, which follow a pattern opposite to the "it's just drama" phenomenon prevalent in pop culture and the post-modern society [37,38], exhibit a significant number of negative emotional posts related to deaths, natural disasters, or conflicts. Terms such as "support", "refugees", "awarded", "combat", and "fire" appear in their word clouds. The presence of negative sentiments aligns with studies that indicate the existence of themes associated with negative polarity, albeit with low frequency [44].

Furthermore, while the emotional content of posts plays an essential role in capturing likes [41], none of the Instagram profiles, which are commonly used by Millennials and Generation Z, show a significant relationship between emotions and likes. However, such a relationship is observed in Twitter to a large extent and in some nations on Facebook. In summary, it reinforces the initial notion that each social media platform fulfills different social needs [45] and/or that virtual communities may not completely overlap.

5.2. Differences between Nations

Previous studies on social networks and the activity of researchers during the COVID-19 period have found significant differences between nations, taking into account Hofstede's cultural model [62]. Thus, culture has been identified as a factor that influences differences among nations in the handling of the pandemic [62]. In the current research, a similar comparative strategy is employed, with culture associated with the corporate communication of each army imprinting heterogeneity on the messages.

In relation to KPIs, it is important to consider the significant differences between nations. Some nations appear to be more active in terms of likes, reactions, and comments. In terms of the quantity of likes, reactions, and comments, India and Israel stand out on Twitter, Instagram, and Facebook, indicating highly active and participatory communities despite significant differences in population (India: 1.408 billion in 2021 vs. Israel: 9.364 million in 2021). However, when it comes to post interactions, India loses its hegemony, and other powerful nations such as Italy, Canada, and Israel take the lead. In terms of the quantity of comments, which represents the moment when citizens respond to posts, India, Israel, and the USA stand out. Previous research has shown that nations such as India, Portugal, and Spain exhibited significantly higher activity on their military profiles during this period [12,13]. Despite cultural differences, the high engagement rates across all nations are consistent with previous research, indicating active participation and the formation of support networks during the outbreak of the pandemic [9,13], creating a culture of support [28,29].

In terms of polarity, there are significant differences between nations on Instagram, while these differences seem to blur on Twitter and Facebook. Overall, all defense profiles exhibit clear communication: positive polarity, objective language, emotional agreement, and a lack of irony. Consequently, their corporate communication deviates from the pop culture commonly used on social media platforms [38,41,44].

With a common invisible enemy showing up [2] and as a globalized and interconnected world [19], it seemed reasonable to expect that the communication strategies of armed forces would be similar across nations. However, the word clouds' results have shown a great diversity in strategic doctrines [19,20] despite sharing the same goal of strengthening their positive image through social media engagement [25].

The results align with previous studies [25,30] indicating that defense communication focuses on showcasing dedication to humanitarian operations, ensuring citizens' security and well-being, and engaging in evacuation and rescue operations. They also convey aspects of their daily lives through corporate identity, national symbols, military spirit, military values, distinctive attributes, professional competence, military discipline, and combat operations.

The novelty of this research is twofold: (a) armies do not approach these themes in a uniform manner due to significant differences in context and organizational culture [26,27]), and (b) the pandemic was not the most important or transcendent theme for these profiles, although it was addressed to varying degrees by most nations.

Thus, the findings support previous authors [33] in highlighting that, in a globalized and increasingly multicultural environment, corporate communication emphasizes a sense of community and addresses the societal feeling of lack of identity. It is also common to use organizational nomenclature or code that generates a distinct corporate concept projecting a global image [30]. Hence, the use of hashtags becomes crucial. The results show frequent acronyms referring to armed forces such as CAD, IDF, or slogans such as the Italian Army's "#noicisiamossempre" ("#wearealways") and "#alserseriziodelpaese" ("#servingthecountry"). Additionally, the incorporation of civil support operations, humanitarian aid, and rescue operations in their discourse, such as India's "nationfirst", Italy's "moretogether", and Australia's "ourpeople", relates to a sustainable and comprehensive leadership approach that seeks social acceptance while inspiring confidence [4]. In other words, it represents a commitment to positive leadership that promotes empathy, personal and social identification, and well-being [6].

Furthermore, managing the digital communication of institutions involves adapting to the virtual environment in a way that aligns with their social and historical context [22,23]. In this regard, the results are consistent with other research, as all the profiles reflect current events, including national conflicts such as those in Israel's Gaza or the dissemination of messages about health and safety measures during the pandemic, as seen in Saudi Arabia. However, it is striking that, despite the widespread involvement in civil support operations related to COVID-19 [3], the armies of Russia and Israel made no mention of the pandemic. In other words, despite the pandemic being a unifying global event, it did not achieve hegemonic significance in defense posts. Additionally, Israel's discourse is noteworthy as it presents a categorization of "us versus them" due to ongoing conflicts, constructing its posts with an in-group versus out-group dynamic, following the principles of social identity theory by Tajfel and Billig [34].

Another transcendental element is the main stakeholder of an organization being society itself, making it essential for actors to collaborate on the construction of the digital community [15,33]. Therefore, it is crucial for the armed forces to analyze which posts received the most likes from their community. Thus, the strategic framework of organizations is based on empathy and adaptation to the collective imaginary and universe and has its own language [31]. Consequently, it is not surprising that there are differences between nations, and it is interesting for defense profiles to pay attention to the preferences of their virtual communities. In this regard, four main groups can be identified: (a) nations with a traditional profile characterized by positive sentiments, objective language, and emotional concordance (Japan, Korea, France, and the USA); (b) nations that react to posts with negative polarity related to natural disasters or dramatic situations (Russia and Poland); (c) nations that react to very positive posts with high emotional diversity, aligning more with the pop culture of social media (Australia and Saudi Arabia); and (d) nations where polarity does not significantly explain the number of likes (Germany, the UK, Canada, Italy, Israel, and India). In other words, there are nations whose digital communities on social media reinforce corporate visions, but it is not synchronous with the vision of their armed forces (Australia, Saudi Arabia, Russia, and Poland). More specifically, the populations of Saudi Arabia and Australia react to traditional posts of digital pop culture with high emotional rates [38], while populations in countries such as the USA, Japan, France, and Korea show more interest in a corporate profile where military-related topics are discussed with positive sentiments [25,30]. On the other hand, Poland and Russia prefer a more distant perspective from the social media profiles of their armed forces, where the military is depicted in its traditional defense roles in complex or insecure situations, rejecting more positive posts that do not focus on those classic functions [41,44].

5.3. Practical Applications

In practical applications of this research, the importance of military profiles collaborating in the construction of the virtual community by paying attention to the language, emotional tone, and topics that their population reinforces through the use of likes is highlighted. Thus, the principles developed by Hallahan [15] are proposed: (a) engaging with the community by generating dialogue, (b) promoting philanthropy, and (c) showcasing social responsibility actions. Similarly, posts with positive sentiments that demonstrate positive leadership are more accepted by the population, as long as the nation is not involved in an armed conflict. However, the change in corporate communication management must start with dialogue, establishing trust and breaking cultural barriers in order to find common ground [32]. The importance of building a sense of digital community in the armed forces is emphasized. This entails the strategic management of corporate communication, aligning the mission with the vision to connect synchronously with the thoughts and sentiments of society.

5.4. Limitations and Prospective Studies

Regarding limitations, it is important to note that the analysis dates correspond to the early stage of the COVID-19 pandemic, representing a specific and highly connected moment. Secondly, it is necessary to determine the existence of differences between temporal phases, as some studies suggest that during the first few months of the pandemic, when social distancing measures were very strict, connectivity increased. Thirdly, the social media platform YouTube was omitted because, during the data collection process, issues were identified that could jeopardize the reliability of the data. The received "likes" may be altered due to the presence of fake profiles that aim to troll cooperative profiles, so such research would benefit from using software such as Graphex to study the community in detail and to exclude profiles that only generate noise. In this sense, as the study relies on data from social media, there may be inherent biases or inaccuracies in the data, which should be acknowledged. Additionally, while this study focused on major military powers, it is unclear whether these findings would extend to smaller nations or non-military organizations. Furthermore, it is necessary to take into account methodological considerations, as indicated by Wei Wei et al. [63]. When dealing with information from a post published on social networks, it is important to approach it from natural language processing (NLP) as a task of natural language understanding (NLU). In this regard, many methods overlook the importance of natural language comprehension. Hence, the need to employ classification methods such as LSTM-SN (Long Short-Term Memory Recurrent Neural Network Fusion Social Network) is proposed [63].

Related to the established limitations, a series of questions arise, leading to future research conclusions: Did the accounts of major military powers exhibit differential behavior during the COVID-19 pandemic compared with that during post-pandemic periods? Are there differences between the pandemic waves? Did the digital community react more during periods of lockdown and social distancing compared with stages of greater normality? What is the behavior of YouTube channels in the profiles of the armies of major military powers? What is the composition of the digital community that follows these accounts? Are there relationships between the communities of different nations?

6. Conclusions

In summary, it is concluded that the profiles of the armed forces of major military powers do not fully align with the preferences of their virtual communities. Military powers offer a highly technical and objective view of their reality, showcasing that their professionalism and technical capabilities are in line with military values. Despite significant differences observed among nations, in general, virtual communities demand positive, subjective, and emotionally diverse posts. In other words, human behavior on social networks requires adherence to a set of social norms that include slang and language from pop culture, as well as a relative "dramatization" of events, while also emphasizing pro-social and altruistic actions.

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