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Two Decades of Emoticons and Emojis in Consumer Behavior Research: Bibliometric Networks, Geographical Atlas and Classical Roots

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ABSTRACT

Emoticons and emojis research have recently witnessed exponential growth. In this article, 261 Scopus peer-reviewed articles related to emoticons and emojis in consumer research are examined using bibliometric techniques. The articles were written by 762 authors from 47 countries over two decades (2000–2023). By so doing, emoticons and emojis research influential authors and journals, emerging trends, collaboration networks, and historical roots are scrutinized. Our findings show that the most relevant outlets publishing Emoticons and emojis research are *Food Quality and Preference, Food Research International, Journal of Sensory Studies, Frontiers in Psychology,* and *Computers in Human Behavior*. Thematic evolution analysis revealed a move away from the well-established emoticons and emojis research themes like "microblog" and "emoticon" to new topics such as "consumer/customer engagement" and "natural language processing". Results also show that there is limited cross-cultural collaboration in emoticons and emojis research. Finally, the "citation classics" of emoticons and emojis research are detected using the reference publication year spectroscopy (RPYS).

Keywords: Emoticons, Emojis, Consumer Behavior, Bibliometrics, RPYS.

INTRODUCTION

Emoticons and emojis have been spreading exponentially in conversations worldwide since the mid-2000s. Currently, 92% of social media users use them and nearly five billion of these characters are sent daily (Baek et al., 2022), with around 700 million daily emojis used on Facebook alone (Buchholz, 2024). These non-verbal cues are usually employed in digital communication to convey ideas, attitudes, and moods (Lu et al., 2016). Nowadays, emoticons and emojis are frequently used in online communication to convey moods, opinions, share experiences, and forge social ties. Recent studies have also shown that emoticons and emojis can be used to create unique emotional associations with the products (Schouteten, Verwaeren, Almli, & Rini, 2022). Like common language, emoticons and emojis adapt to new realities. For example, during the COVID-19 pandemic, neologisms like "teleworking" and "vaccinosceptic" became common and were matched by emojis as "the masked face" and the "letterbox" (for parcel deliveries). Such characters can also adapt to cultural changes. For example, in Spain, emojis representing *la fiesta* are the most widely used, whereas in France, hearts' emojis enjoy great popularity, corroborating the "French lover cliché" (Cini, 2022, p. 31).

First used in Japan in 1986, emoticons, short for emotion icons, use different characters to represent facial expressions. Emoticons have become popular with the advent of the Internet and SMS text messaging via mobile devices in the late 1990s. An emoji also represents "an iconic, visual representation of an idea, entity, feeling, status, or event, that is used alongside or instead of words in digital messaging and social media" (Evans, 2015, p. 1). Although both emoticons and emojis can visually refer to the same content and may even allude to the "same communicative function" (Prada et al., 2018, p. 1927), there are two major technical differences between emoticons and emojis (Volker & Mannheim, 2021). First, while the first is limited to the imagery that the standard keyboard can create, the latter can depict any visual imagery. Second, while emoticons consistently look the same as they are produced through keyboard characters, emojis usually look different across platforms. Thus, nowadays, emojis are generally replacing emoticons as they are regarded as more “aesthetically appealing, familiar, clear and meaningful” (Rodrigues, Prada, Gspar, Garrido, & Lopes, 2018, p. 401). Because emojis encompass many more facial features (Coyle & Carmichael, 2019) and can better convey emotional state of mind (Ganster, Eimler, & Kramer, 2012), they have been used extensively for a variety of purposes including maintaining relationships, conveying complex sentiments, and reducing interpersonal distance (Cramer, De Juan, & Tetreault, 2016; Gibson, Huang, & Yu, 2018; Skovholt, Gronning, & Kankaanranta, 2014).

Recently, the use of emoticons and emojis has been extensively investigated. For example, McShane, Pancer, Poole, and Deng (2021) demonstrated that the use of emojis in tweets increases brand engagement on Twitter as measured by increased likes and retweets. Vidal, Ares, and Jaeger (2016) found that more than one-fifth of the eating-related tweets included an emoji related to hand gestures or facial expressions, implying that they are being used spontaneously to signify emotional reactions to food or beverages. Similarly, Jaeger et al. (2017) found that emojis might be used to elucidate emotional associations with several product categories, including juice, cheese, chocolate, and honey. This finding led the authors to suggest the use of emoji surveys to measure food-related consumer emotions. Consumer research has generally suggested that the use of emoticons and emojis can enhance brand attachment (Arya, Sethi, & Verma, 2018), brand image and credibility (Beattie, A. Edwards, & Edwards, 2020; Daniel & Camp, 2020), and purchase intention (Casado-Molina, Rojas de Garcia, Alarcon-Urbistondo, & Romero-Charneco, 2022; Das, Wiener, & Kareklas, 2019). The justification for such effects is mainly based on the emotional contagion theory (Lohmann, Pyka, & Zanger, 2017), arguing that consumers tend to catch the emotion expressed by the emoji.

However, despite the proliferation of emoticons and emojis research in consumer behavior, to the best of our knowledge, virtually no bibliometric reviews have been conducted to examine this research domain. A notable exception is Bai, Dan, Mu, and Yang (2019). However, the authors of the study focused only on 167 emoji papers and did not conduct a comprehensive bibliometric analysis. Thus, we argue that filling this research gap makes three major contributions to the literature. First, by conducting this bibliometric analysis, we expand on the prior bibliometric literature examining other research domains (Zhu & Hua, 2017). Second, by applying a network methodology to investigate emoticons and emojis usage in consumer behavior, we contribute significantly to prior literature examining information diffusion dynamics. Finally, by tracing the development of the emoticons and emojis research in consumer behavior over two decades, we also add to the emerging literature examining the application of the emoticons and emojis research in areas as diverse as service failures (Liu, Lv, & Huang, 2023), tipping behavior (Lefebvre, Boman, & Orlowski, 2024), reaction to advertising (Das et al., 2019), and evaluating food products (Schouteten, Verwaeren, Gellynck, & Almli, 2019). More specifically, the aim of this research is to answer the following questions:

1. What is the evolution pattern of scholarly emoticons and emojis research in consumer behavior?
2. Who are the most relevant authors and journals publishing the “core” emoticons and emojis research?
3. What are the major hot spots in emoticons and emojis research?
4. What are the main patterns in the emoticons and emojis research collaborative networks?

This research is organized as follows. In Section Two, I have described the method followed to conduct the analysis. In Section Three, I have presented the research results. In Section Four, I have discussed the results, whereas the last section focuses on the research limitations and identifies possible future research avenues.

METHODOLOGY

To carry out the analysis, I have followed a five-step procedure :

1. Accessing the designated database and selecting the keyword search keywords.
2. Performing the basic bibliometric analysis.
3. Conducting the major network analyses.
4. Charting the basic thematic maps.
5. Tracking the “classical roots” of the emoticons and emojis research using the RPYS analysis.

Several software packages were used to carry out the study, including the R 4.2 (The R Core Team, 2024) and the VOSviewer (van Eck & Waltman, 2019). We briefly highlight the major steps outlined above here.

Database and Document Extraction

The Scopus database was used to access published documents on emoticons and emojis research in consumer behavior. The author opted for this database because it has been extensively used in bibliometric studies. I used the search terms “emoticon” OR “emoji” AND “consum” OR “customer” OR “adopt” OR “purchase” in the title, abstract, or keywords section. In this study, the researcher focus solely on research published in English. There has been extensive debate as to which documents should be selected for conducting bibliometric research. Here, I opted only peer-reviewed articles. The search process implemented is shown in **Figure 1**. **Table 1** shows a summary of the data collected.

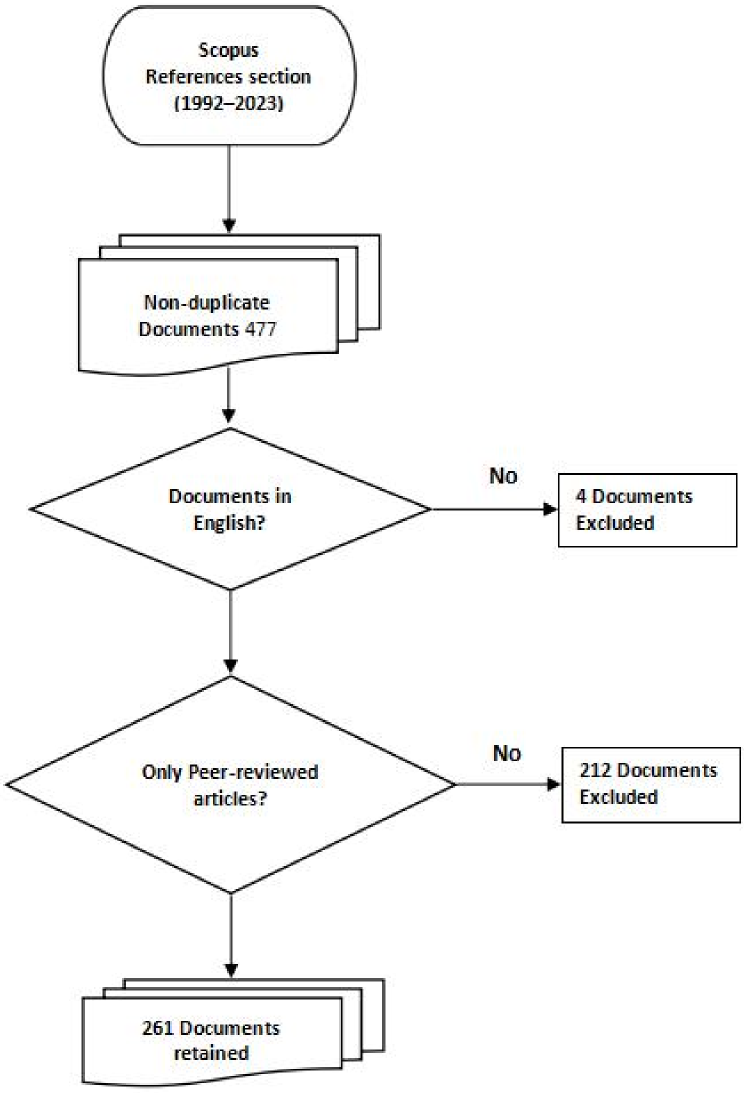

Figure 1. Emoticons and Emojis in Consumer Behavior Research Search Flow Chart

Table 1. Main Information about Emoticons and Emojis in Consumer Behavior Research Data

Description	Results
MAIN INFORMATION ABOUT DATA	
Timespan	2000–2023
Sources (Journals, Books, etc.)	183
Documents	261
Annual Growth Rate %	19.31
Document Average Age	3.8
Average citations per doc	20.61
References	13030
DOCUMENT CONTENTS	
Keywords Plus (ID)	1070

Description	Results
Author's Keywords (DE)	899
AUTHORS	
Authors	762
Authors of single-authored docs	35
AUTHORS COLLABORATION	
Single-authored docs	37
Co-Authors per Doc	3.42
International co-authorships %	23.75
DOCUMENT TYPES	
Article	261

From the table, it can be seen that 261 peer-reviewed articles written by 762 authors were extracted. Only 37 articles were written by single authors, and the documents encompass 13,030 references.

Bibliometric Network Analysis

Knoke and Yang (2010, p. 8) defined a network as "a structure composed of a set of actors, some of whose members are connected by a set of one or more relationships." Khan and Wood (2016, p. 388) noted that analyzing existing literature from a social network analysis (SNA) perspective can "reveal valuable invisible patterns that can facilitate theory development and uncover areas for future research." Network analysis has recently been extensively employed in bibliometric studies to explore keywords co-occurrence networks (Banckendorff, 2009) and scientific collaborative initiatives (X. Chen & Liu, 2020; Ding, 2011; Glänzel & Schubert, 2005; Zou, Yue, & Vu, 2018).

Thematic Maps

First introduced by Law, Bauin, Courtial, and Wittaker (1988), a thematic map is used to examine the evolution and dynamics of specific research clusters through the analysis of keyword co-occurrence (Gonzales-Valiente, 2019). This map is usually formed based on the Callon, Courtial, and Laville (1991) density and centrality indicators. Within this context, centrality measures a theme's importance, whereas density measures a theme's development within a research field. Ávila-Robinson and Wakabayashi (2018) noted that the thematic map is akin to financial portfolio analysis diagrams. This map has been widely employed in bibliometric studies.

RPYS

RPYS aims to "quantify the significance of historical publications and to reveal the historical roots of a given research field". Since RPYS focuses on analyzing the references, it can be regarded as a "backward" analysis of citations (Thor, Marx, Leydesdorff, & Bornmann, 2018, p. 592). The method starts by extracting all cited references in a research domain. In the next step, cited references deviation from a 5-year median period is calculated. Finally, software is used to calculate the frequently cited historical publications.

RESULTS

Emoticons and Emojis Research Evolution

261 Scopus-indexed documents pertinent to the emoticons and emojis research in consumer behavior were extracted. **Figure 2** displays the evolution of this research domain over time. The graph shows a general growth rate of 19.31%. In the first period (2000-2014) there was virtually no growth in emoticons and emojis in consumer behavior research with a maximum of one document annually. This period represents the initial stage in the emoticons and emojis usage in consumer behavior research. The next period (2015–2019) seems to represent "the steady growth stage" as it witnessed considerable growth in emoticons and emojis research in consumer behavior production, with documents published ranging between eight and twenty-one. The final period (2020–2023) seems to represent the "rapid growth stage" as the emoticons and emojis research in consumer behavior reached the "peak" stage, with documents published ranging between thirty-four to fifty-eight per year.

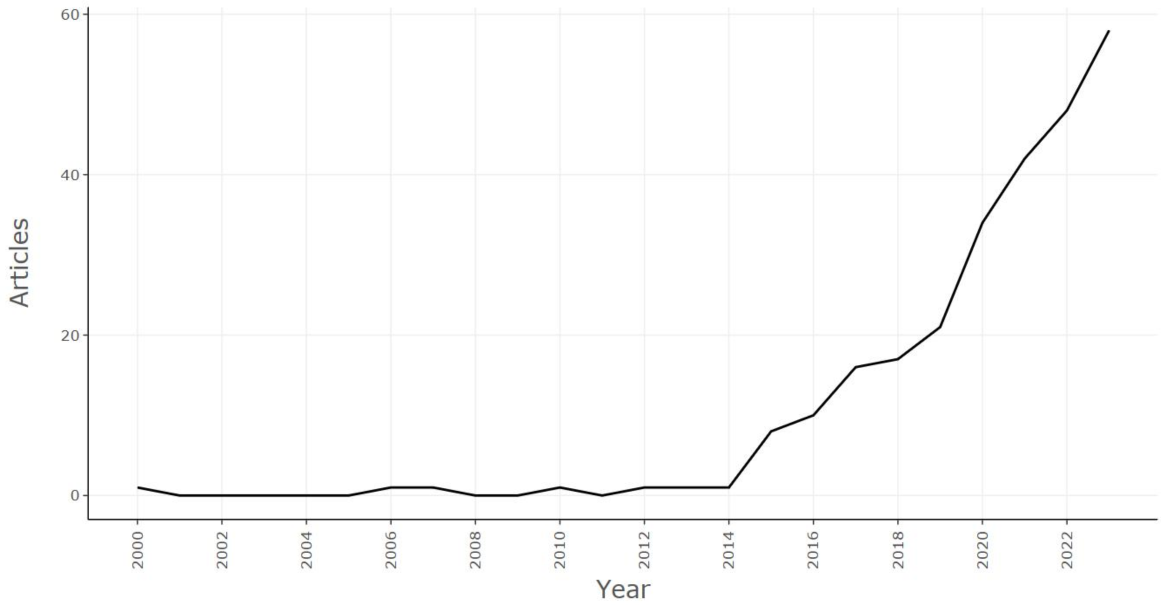

Figure 2. Emoticons and Emojis in Consumer Behavior Research Production over Time

The most relevant journals publishing emoticons and emojis research in consumer behavior are presented in **Table 2**. The table shows that *Food Quality and Preference* (16 articles), *Food Research International* (12 articles), *Journal of Sensory Studies* (8 articles), *Frontiers in Psychology* (6 articles), and *Computers in Human Behavior* (5 articles) are the most relevant sources in this regard.

Table 2. Most Relevant Journals Publishing Emoticons and Emojis in Consumer Behavior Research

Sources	Articles
Food Quality and Preference	16
Food Research International	12
Journal of Sensory Studies	8
Frontiers in Psychology	6
Computers in Human Behavior	5
Foods	5
Journal of Business Research	4
Sustainability (Switzerland)	4
International Journal of Recent Technology and Engineering	3
Journal of Research in Interactive Marketing	3
PLoS ONE	3
Applied Marketing Analytics	2
Australasian Marketing Journal	2
Decision Support Systems	2
Discourse and Communication	2
IEEE Access	2
International Journal of Research in Marketing	2
Journal of Advertising	2
Journal of Politeness Research	2
Journal of Product and Brand Management	2

Table 3 shows the most globally cited articles on emoticons and emojis in consumer behavior research. From the table, we see that Chew and Eysenbach's (2010) article tops the list with 1166 citations. This article used an archive of over two million tweets to examine public sentiment toward the swine flu or H1N1 pandemic. The study found that Twitter can be used as a reliable method in "infodemioloy" research. With 222 citations, Wolf's (2004) article examined how emoticons are used to reinforce stereotypical gender roles in online newsgroups. X. Li, Chan, and Kim (2019) is the third most widely cited article on emoticons and emojis in consumer behavior with 140

citations. This experimental study showed that consumers perceive service providers who use emoticons as higher in the warmth dimension but lower in terms of the competence dimension.

Table 3. Most Globally Cited Emoticons and Emojis in Consumer Behavior Articles

Paper	Total Citations	TC per Year	Normalized TC
Chew C, 2010, PLOS ONE	1166	77.73	1.00
Wolf A, 2000, CYBERPSYCHOL BEHAV	222	8.88	1.00
Li X, 2019, J CONSUM RES	140	23.33	5.28
Asghar MZ, 2017, PLOS ONE	123	15.38	2.65
Vidal L, 2016, FOOD QUAL PREFERENCE	121	13.44	3.52
Vandergriff I, 2013, J PRAGMAT	116	9.67	1.00
Hsieh SH, 2017, COMPUT HUM BEHAV	107	13.38	2.30
Vidal L, 2015, FOOD QUAL PREFERENCE	102	10.20	2.52
Das G, 2019, J BUS RES	96	16.00	3.62
Page R, 2014, J PRAGMAT	92	8.36	1.00

Another way to look at the most influential authors in a research domain is known as the dominance factor. This metric can be easily calculated by dividing the number of multi-authored articles in which the author is the first author by the total number of multi-authored articles. Because of its objectiveness, this measure was employed in several bibliometric studies (Elango & Rajendran, 2012; Firdaus et al., 2019). **Figure 3** reveals the most dominating authors in the field of emoticons and emojis research over the study period. From the graph, we see that the most dominating authors in this field are S. Jaeger (2015–2023), G. Ares (2015–2023), and L. Vidal (2015–2023). However, some newcomers have also achieved some domination. Examples include Y. Li (2021–2023) and S. Fuentes (2020–2023).

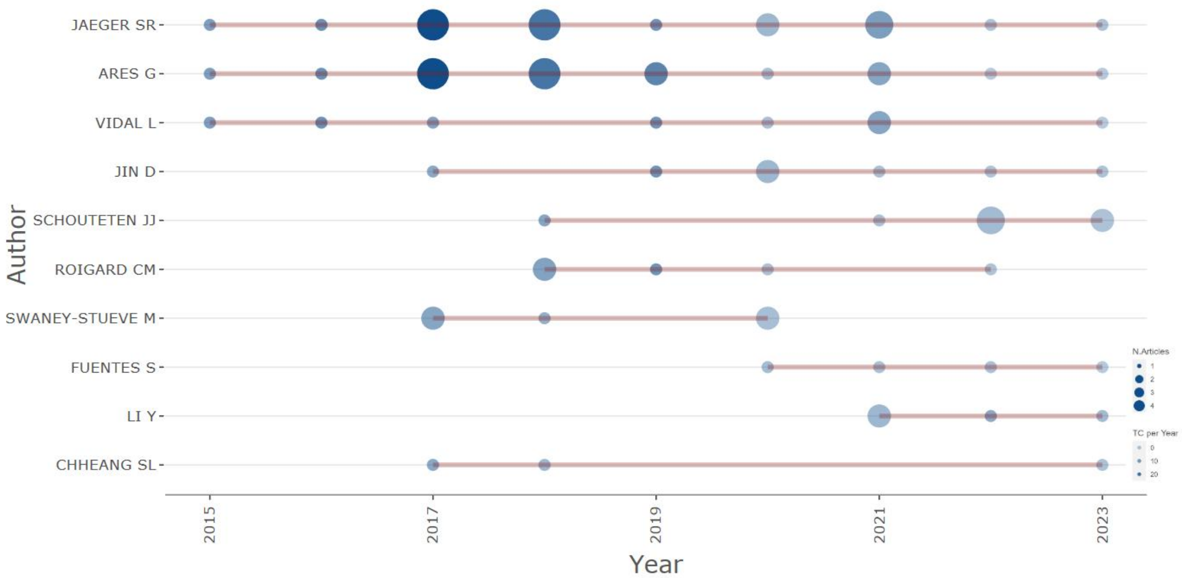

Figure 3. Emoticons and Emojis in Consumer Behavior Research Author Dominance over Time

Evenness or “concentration of authors’ contribution” is another measure based on Lotka’s law arguing that “the number of authors producing a certain number of articles is a fixed ratio, 2, to single-article authors.” **Figure 4** shows Lotka’s law in the emoticons and emojis in consumer behavior research, which implies that Lotka’s law does hold in this research domain (2-sample test *Kolmogorov-Smirnov* $p > 0.05$).

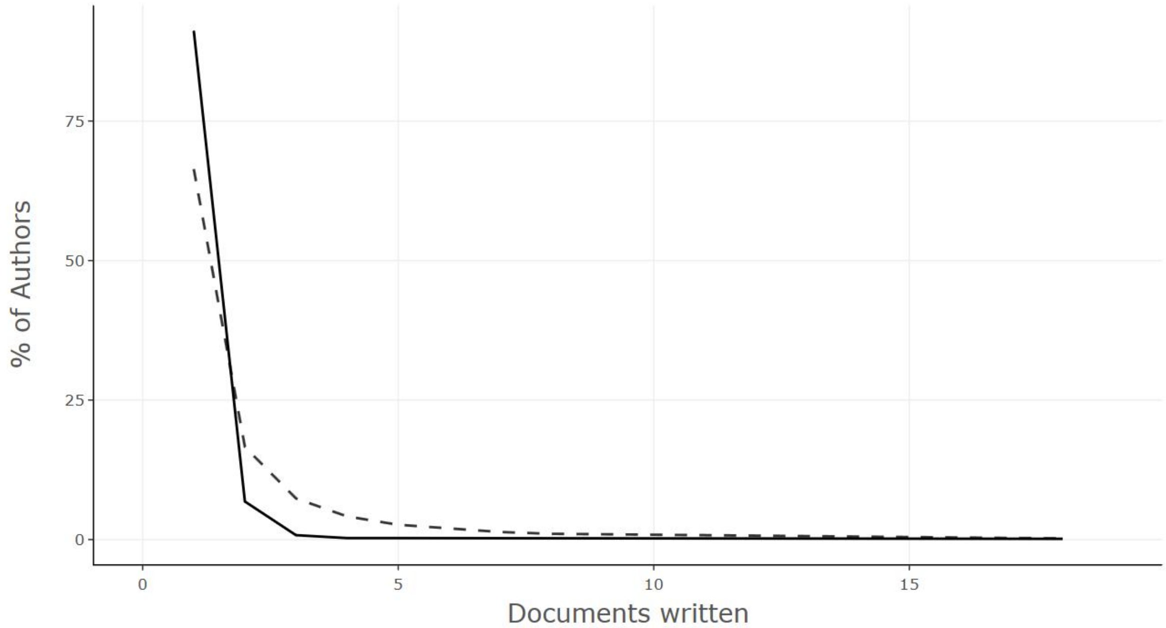

Figure 4. Lotka's Law in Emoticons and Emojis in Consumer Behavior Research

Network analysis

Co-citation Networks

Fang, Wei, and Wang (2023) argued that a co-citation network is mainly utilized to detect the intellectual kinship between two documents. Thus, if two authors are cited together in a third document, they are deemed related. **Figure 5** plots the emoticons and emojis research in the consumer behavior co-citation network. The network reveals four distinct clusters, each with its authors and its thematic focus. Wider et al. (2023, p. 3) argued that co-citation networks facilitate "the identification of the most influential works and prevalent topics in the field." For example, from the graph, we see that the red cluster includes 40 authors like M. Danesi and J. Walther. The green cluster encompasses 21 authors such as G Ares and S Jaeger. The two authors appear to be the most prominent within this cluster as they are centrally positioned in the network. Such authors anchor each community and they have a large impact on other communities as they control and stimulate information diffusion [in the network] through research activities. Some nodes in the graph are very close to each other, indicating a strong "homophily effect" (McPherson, Smith-Lovin, & Cook, 2001). Jiang, Ritchie, and Benckendorff (2019) indicated that homophily implies a "disciplinary or thematic similarity." For example, G Ares and S Jaeger's nodes in the green cluster appear to be quite close to each other, suggesting a "homophily effect." The yellow cluster includes authors like A Cardello and A Gimenez, whereas the blue cluster encompasses eight authors as R de Wijk and C de Graaf.

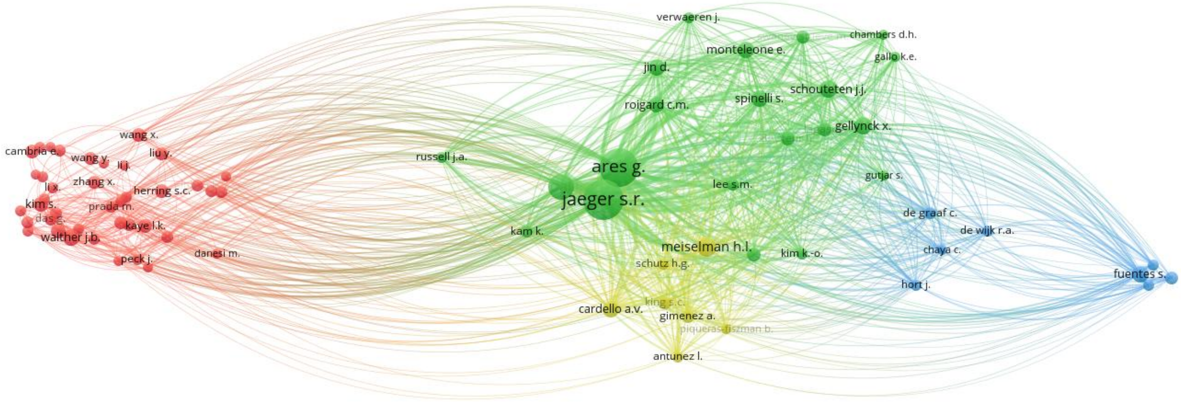

Figure 5. Emoticons and Emojis in Consumer Behavior Author Co-citation Network

Bibliographic Coupling

First introduced by Kessler (1963), bibliographic coupling occurs when two articles have a shared third article in their reference list, whereas the coupling strength is determined by the number of shared cited articles (Wei, Wang, Chen, Yu, & Liao, 2018). Fomina, Glinska-Newes, and Ignasiak-Szulc (2022, p. 298) argued that this technique can detect “semantic similarities of publications based on the references they have in common.” In this paper, we used the fractional counting method to construct the bibliographic coupling network. Unlike the full counting method, in fractional counting, the weight of a link is fractionalized to minimize the impact of long-reference list publications such as review articles. Following Sadeghi-Niaraki (2023), we conducted the bibliographic coupling based on authors and countries where network visualizations have been used to represent the bibliographic coupling for both. In such networks, the relative importance is denoted by the label size, and relatedness of shared references is denoted by the link.

Using this technique, ten clusters were formed for authors as shown in **Figure 6**. These clusters represent the major research themes of emoticons and emojis in consumer behavior. For example, the biggest cluster (in red) included 30 contributions from authors like Ma and Wang (2021), L. Smith and Rose (2020), Das et al. (2019), Hsu and Chen (2020), Y. Li and Shin (2023) and Moussa (2019). A closer manual inspection of all the articles in this cluster reveals that the major theme examined by these authors deals with how emoticons and emojis influence consumer satisfaction/purchase intention. For example, Ma and Wang (2021) examined the impact of emoticon type on consumers’ satisfaction and re-purchase intention in a service failure context. The authors found that “the presence of a negative emoticon in a response is more sincere and generates a higher level of forgiveness than those responses that use positive emoticons.” (p. 443). Relying on the theories of emotion as social information and emotional contagion, L. Smith and Rose (2020) reported a positive consumer’s affective response to smiley-face emojis. Das et al. (2019) investigated how consumers’ purchase intentions are affected by the use of emojis in advertisements. Results show that the presence of emojis leads to a higher level of purchase through the higher positive effect experienced by the consumer.

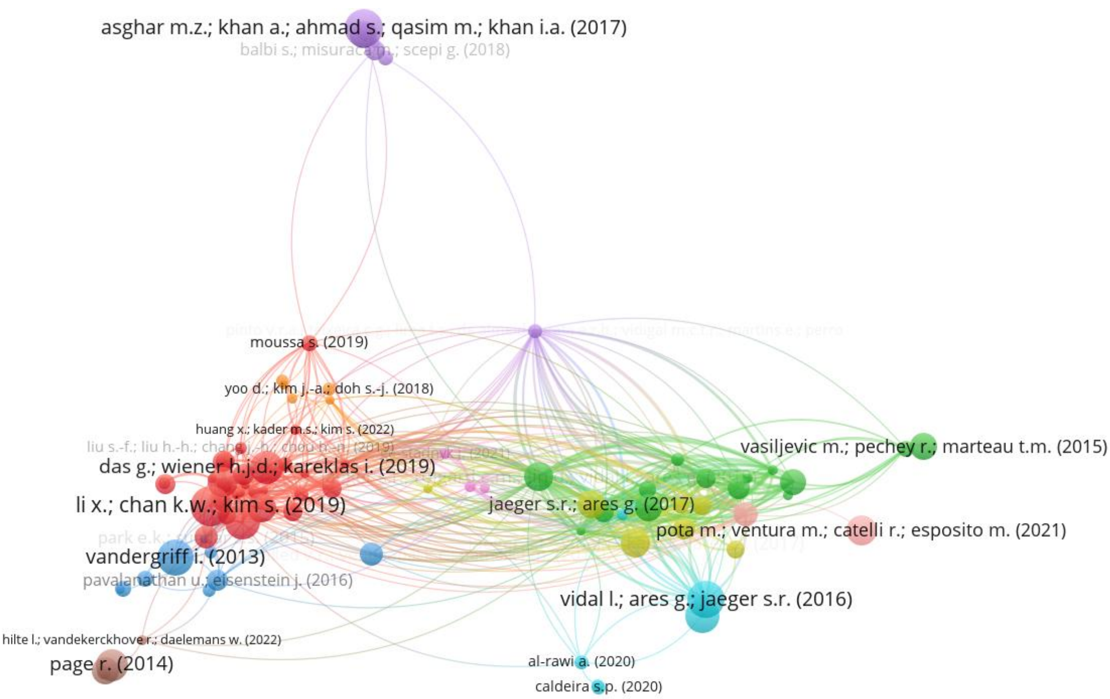

Figure 6. Emoticons and Emojis in Consumer Behavior Author Bibliographic Coupling Network

Figure 7 presents the bibliographic coupling by countries involved in emoticons and emojis in consumer behavior. From the graph, it is evident that the US dominates the research production in this field although the exchange between it and other nations is not strong. The graph shows 4 different clusters with 20 nations. The largest cluster includes the UK, Canada, France, Japan, Italy, India, and Saudi Arabia. The second cluster includes 6 nations (the USA, Australia, China, Hong Kong, Taiwan, and Spain), whereas the third cluster includes Norway, the Netherlands, Belgium, Brazil, New Zealand, and Uruguay. The remaining cluster is an "isolate" and includes only South Korea.

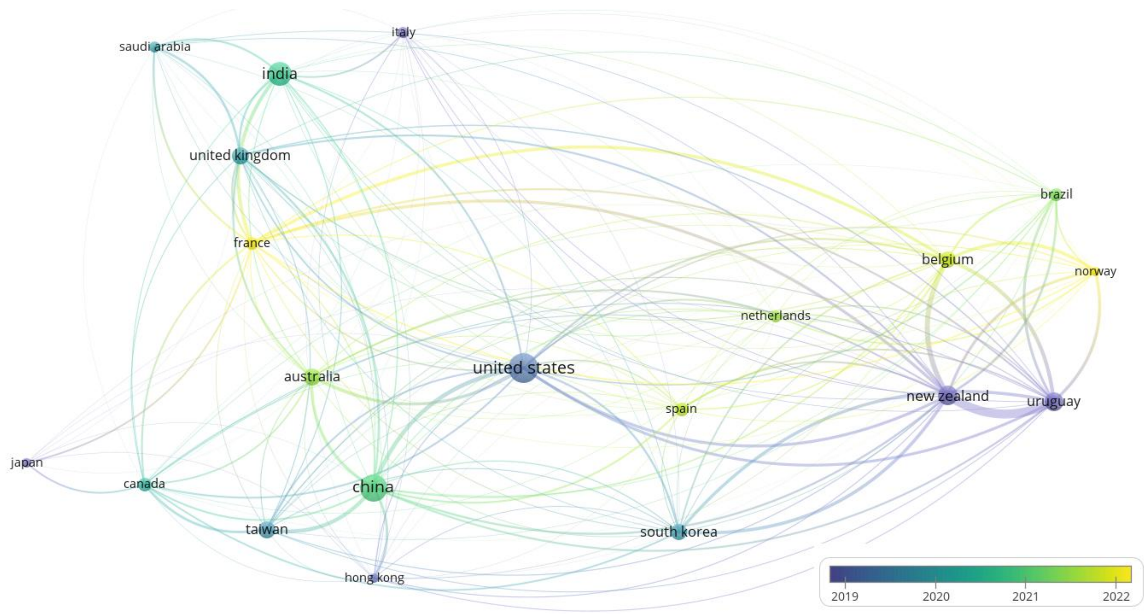

Figure 7. Emoticons and Emojis in Consumer Behavior Countries' Bibliographic Coupling Network

Collaboration Networks

Figure 8 depicts the collaborative initiatives among nations. The graph shows a total of 32 such initiatives in seven clusters. The largest red cluster encompasses countries like China, Hong Kong, Taiwan, and Macao. The green cluster includes countries like Sweden, Norway, and Denmark, whereas the blue one encompasses countries like the US, Mexico, and Australia. The yellow cluster includes four nations (France, Belgium, Canada and Japan). The orange cluster includes India, Italy, and Lithuania, whereas the purple cluster encompasses Ghana, Pakistan, Saudi Arabia, and the United Kingdom. Finally, the light blue cluster includes four nations, namely New Zealand, Uruguay, Brazil, and South Korea cluster encompasses France and Romania. A closer look indicates that most of the clusters are formed based on linguistic similarity, cultural affinity, or geographic proximity. **Figure 9** shows the strength of the collaboration initiatives among nations. From the graph, we see that the strongest cooperation (14 initiatives) occurs between New Zealand and Uruguay, followed by the cooperation between the United States and China (4 initiatives). Three cooperation initiatives took place between France and Belgium, France and India, and New Zealand and Belgium.

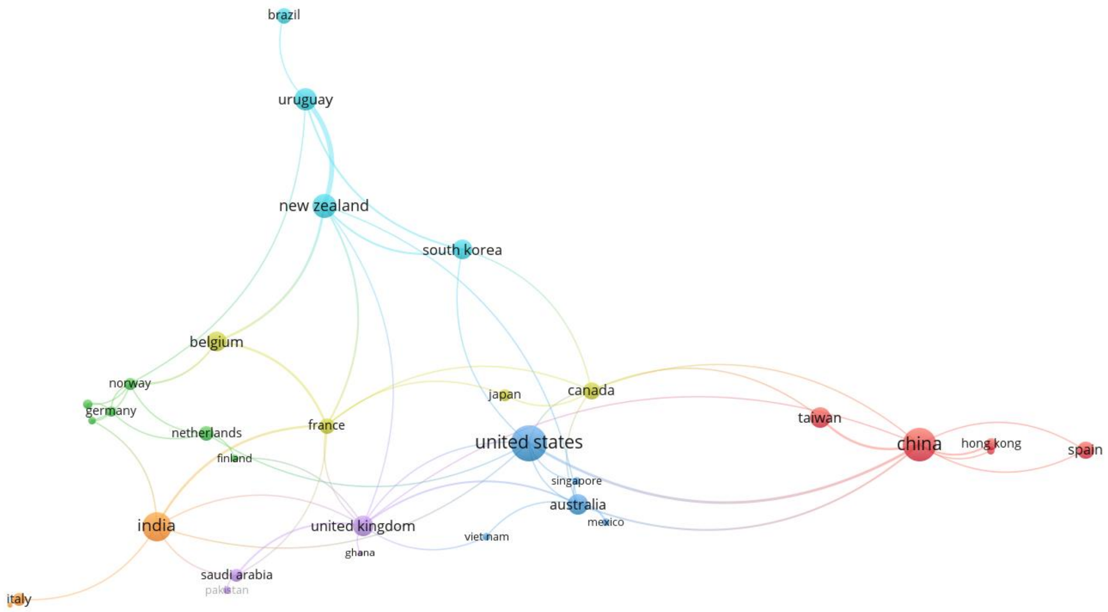

Figure 8. Emoticons and Emojis in Consumer Behavior Countries' Collaboration Network

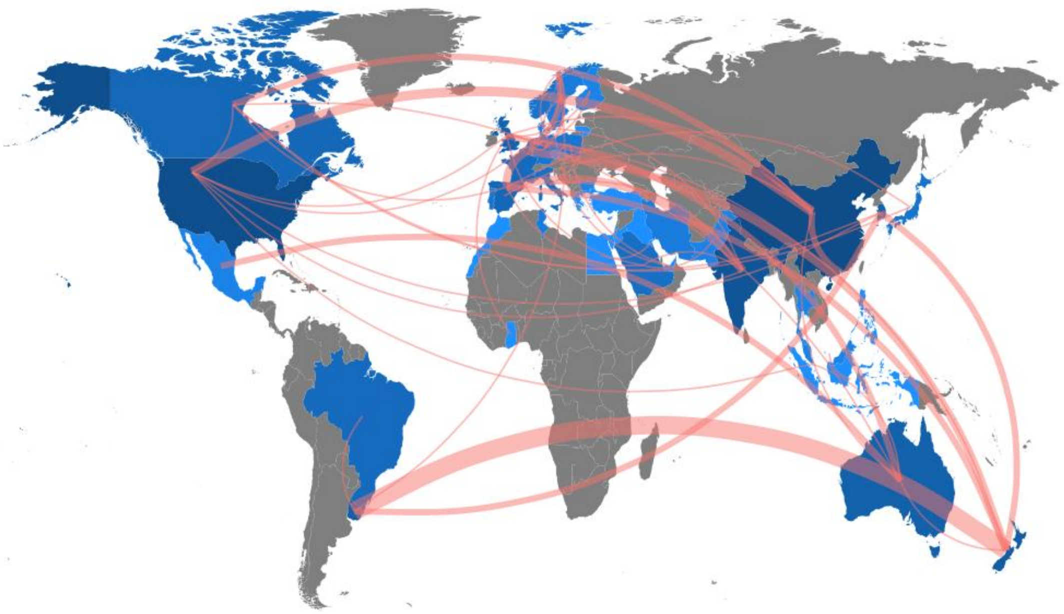

Figure 9. Emoticons and Emojis in Consumer Behavior Countries' Collaboration Map

Keywords and Co-word Network Analysis

C. Chen, Song, Yuan, and Zhang (2008) argued that keywords can be utilized to detect a paper's main theme. **Figure 10** summarizes the emoticons and emojis research based on "author-provided keywords." In a wordcloud, the significance and importance of each word are determined by its closeness to the center of the cloud (Liao, Tang, Li, & Lev, 2019). The graph reveals that the most significant keywords used in the emoticons and emojis research are "emoji(s)" (63 times), "social media" (36 times), "emoticons" (23 times), "sentiment analysis" (20 times) and "Twitter" (17 times).

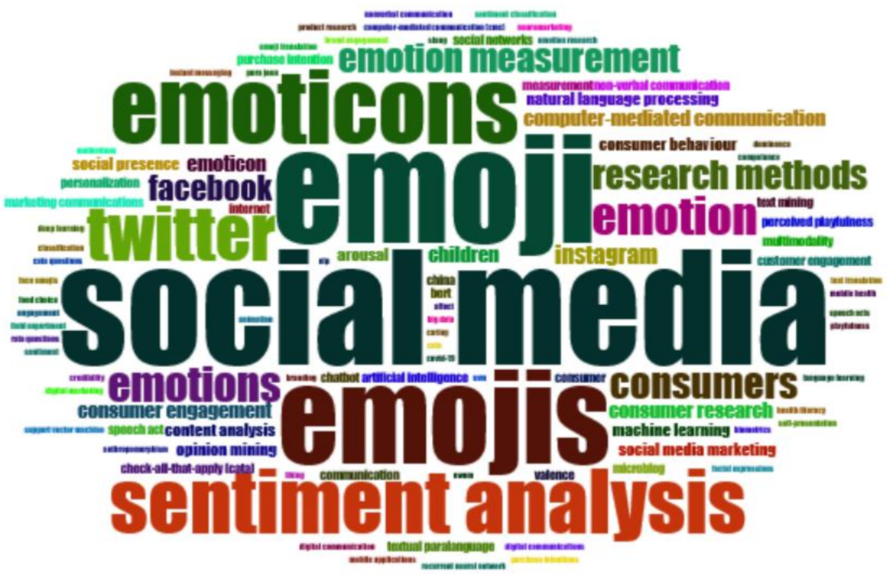

Figure 10. Emoticons and Emojis in Consumer Behavior Author-provided Wordcloud

Keywords provided by authors were used to construct a keyword co-occurrence network for emoticons and emojis in consumer behavior research. We opted for keywords provided by authors since "authors of a paper should be the ones that have the best feel as to what areas are spoken to by the paper" (Corbet et al., 2019). The co-occurrence network obtained is depicted in **Figure 11**. The figure shows seven distinct clusters. For instance, the largest cluster in red includes nine keywords and seems to deal with consumer engagement with emoticons and emojis. This cluster includes keywords such as "customer engagement", "consumer engagement", and "social media marketing." The green cluster includes eight keywords and appears to deal with emoticons and emojis text analytics. This cluster includes keywords such as "machine learning", "natural language processing", and "text mining." The blue cluster includes seven keywords and seems to deal with measuring consumer reactions to emoticons and emojis. This cluster includes keywords such as "consumers", "emotion measurement", and "measurement." The yellow cluster also encompasses seven keywords such as "social networks", "Instagram," and "Internet" and appears to deal with the use of emoticons and emojis on social media platforms. The purple cluster includes six keywords and appears to deal with measuring consumer valence. This cluster encompasses keywords such as "consumer", "arousal", and "valence." The light blue cluster appears to focus on purchase intention. This cluster contains keywords like "social presence", "emoticon", and "purchase intention." Finally, the orange cluster includes only five keywords such as "chatbot" and "social media." This cluster appears to deal with the use of emoticons and emojis to augment new technology.

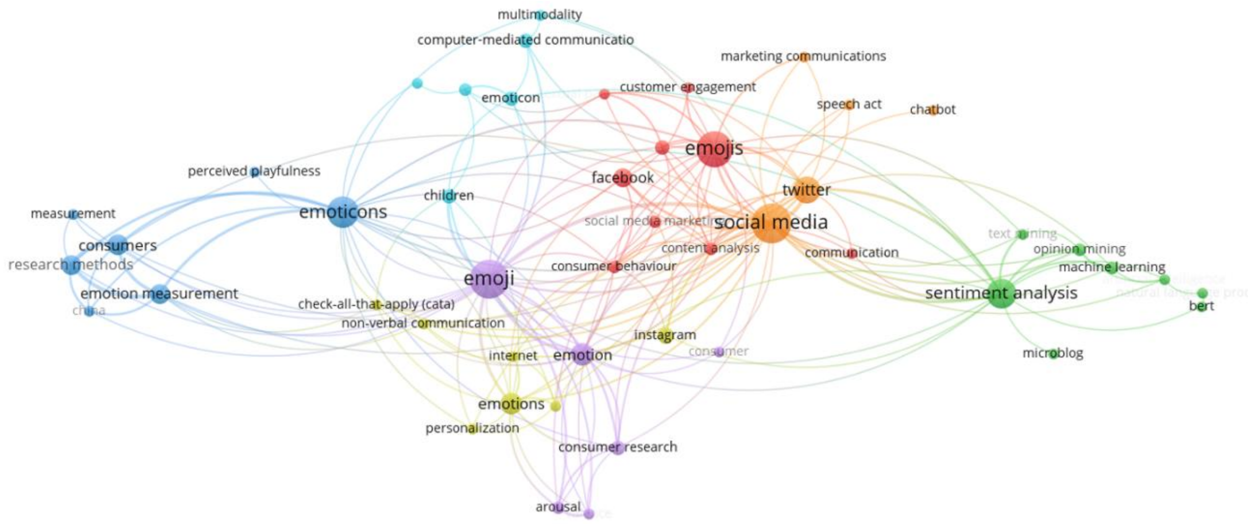

Figure 11. Emoticons and Emojis in Consumer Behavior Keyword Co-citation Network

A Sankey plot was also constructed to trace the authors-keywords-sources links. **Figure 12** depicts the emoticons and emojis research Sankey/three-field plot. From the diagram, we see that the largest edge widths flow from keywords like “emoji”, “emoticon(s)”, “consumers”, and “social media.” The diagram also reveals that certain authors use disproportionally larger numbers of keywords, signifying the diversity of their research (e.g., S. Jaeger and G. Ares) compared to others (e.g., S. Moussa and S. Fuentes).

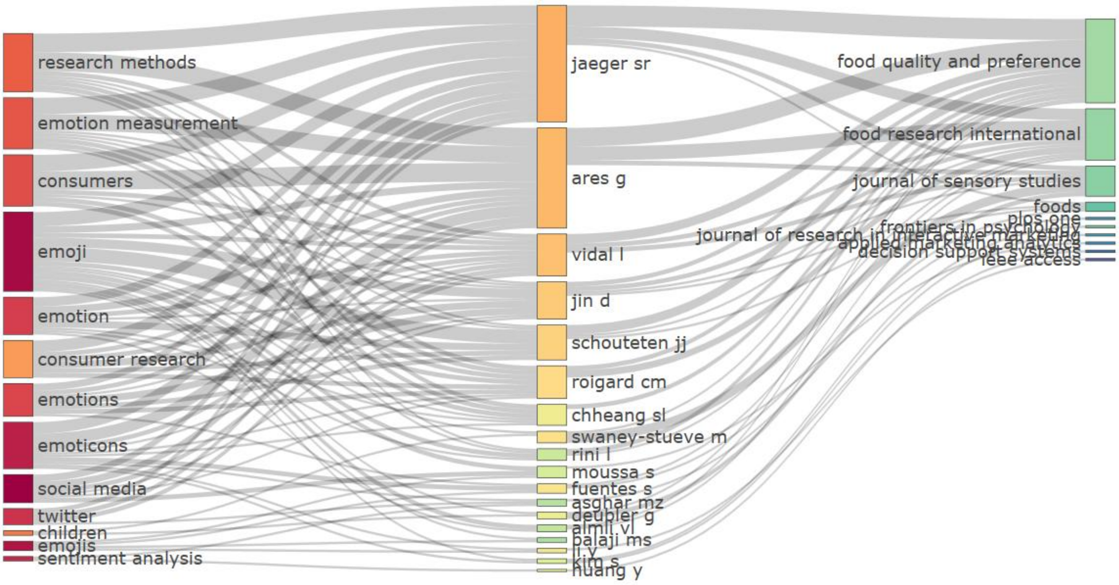

Figure 12. Emoticons and Emojis in Consumer Behavior Sankey Diagram

Trending Topics and Thematic Evolution

Figure 13 plots the trending emoticons and emojis research topics. The figure shows a move away from the well-established emoticons and emojis research themes like “microblog” (2016–2018) and “emoticon” (2017–2018) to new topics such as “consumer/customer engagement” (2022–2023) and “natural language processing” (2023). This sudden burst in the emoticons and emojis research can be regarded as a “hotspot” or new frontier in this field of research (Neff & Corley, 2009; van Eck & Waltman, 2014). Thus, such new themes might imply “potential fronts” in the emoticons and emojis research (Qian, Law, & Wei, 2019).

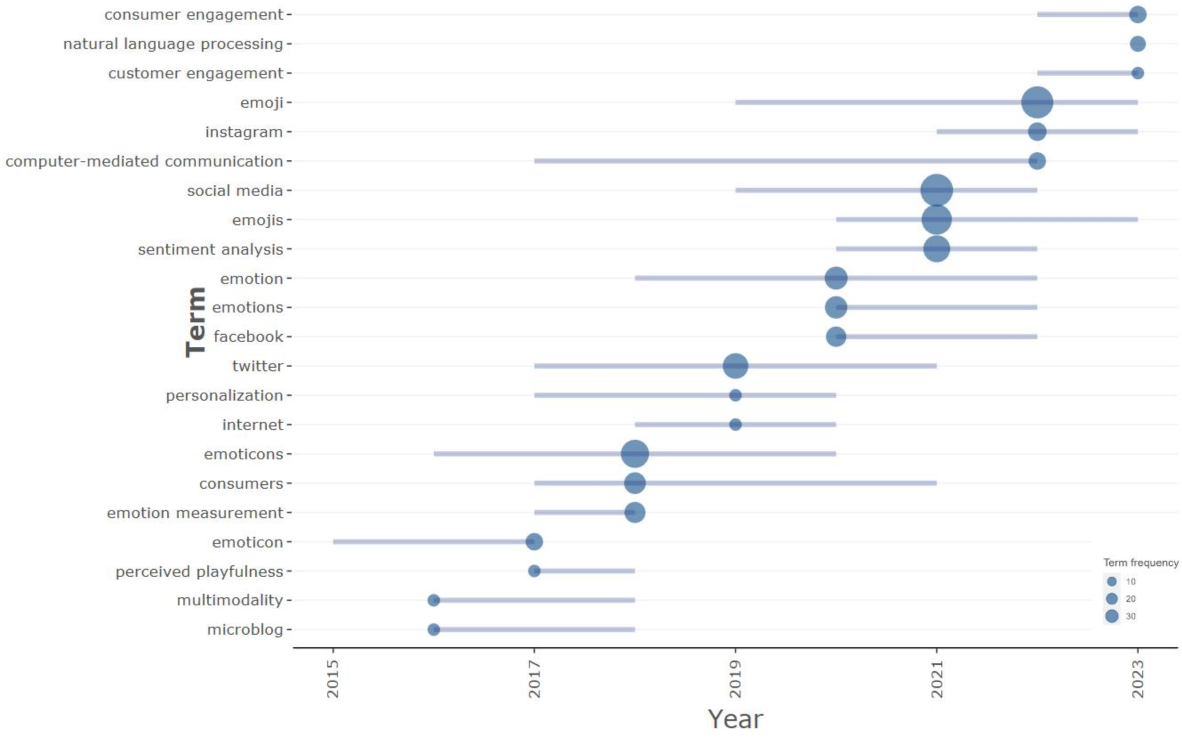

Figure 13. Emoticons and Emojis in Consumer Behavior Model Trending Topics/Themes

Thematic Maps

Figure 14 depicts a thematic or strategic map for the emoticons and emojis research. “Motor themes” shown in the first quadrant represent both internally and externally well-developed themes. Such themes are characterized by high centrality and high density (Cobo, Lopez-Herrera, Herrera-Viedma, & Herrera, 2011). In emoticons and emojis research, themes like “emojis” and “computer-mediated communication” belong to this quadrant. The second quadrant encompasses niche themes. In the emoticons and emojis research, themes like “brand engagement” and “emoji translation” belong to this quadrant. The third quadrant, with themes like “face emojis” deals with “emerging or declining themes.” Themes within this quadrant might be regarded as potential hotspots in emoticons and emojis research. The fourth quadrant deals with the “basic and transversal themes.” In the emoticons and emojis research, examples include “social media”, “sentiment analysis”, and “Twitter.”

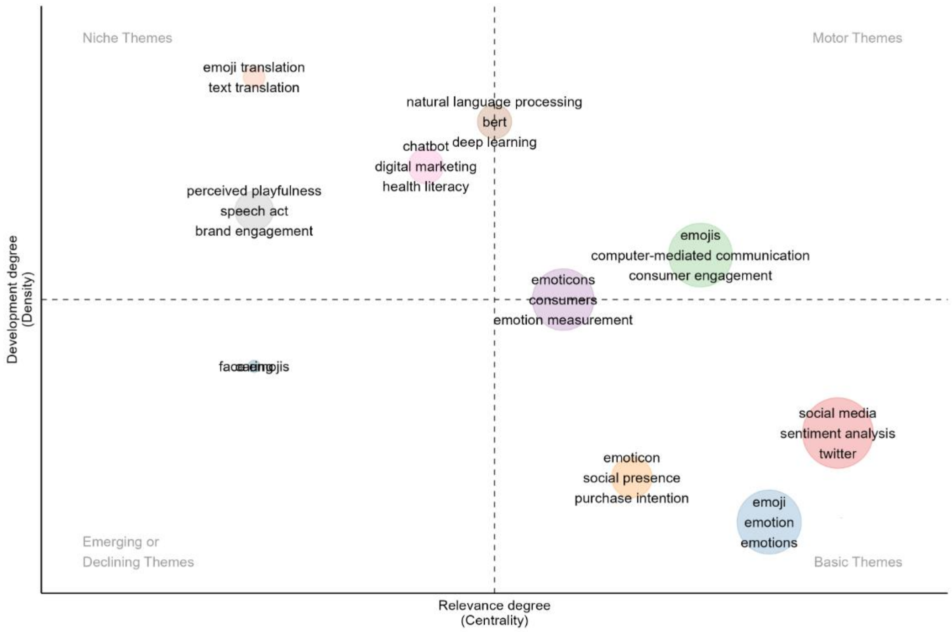

Figure 14. Emoticons and Emojis in Consumer Behavior Model Thematic Map

RPYS Results

The CRExplorer software was used to import the references listed in the 261 articles (13,030 references). **Figure 15** plots the emoticons and emojis research spectrogram. The number of cited references is shown in a black line and the 5-year deviation from the median is shown in red. Analyzing the peaks in the red line can be used to reveal the "citation classics" forming the historical roots of the emoticons and emojis research. This is because such peaks are of "specific significance to the research field in question and often represent its origins and intellectual roots" (Marx, Haunschild, Thor, & Bornmann, 2017, p. 337). The figure shows that the earliest citations were as old as 1835 with some historical sources such as the early Scottish business theorist Andrew Ure's (1835) "*The Philosophy of Manufactures: or, An Exposition of the Scientific, Moral, and Commercial Economy of the Factory System of Great Britain*." In this treatise, Ure described the new industrial system developed in England and argued that the people of England benefited greatly from the Industrial Revolution. Classical citations laying the foundation of emoticons and emojis research also include Gustave le Bon's book "*The Crowd: A Study of Popular Mind*" (1896) and Gabriel Tarde's Book "*Laws of Imitation*" (1903). **Table 4** shows the major peaks in emoticons and emojis research along with the year of occurrence.

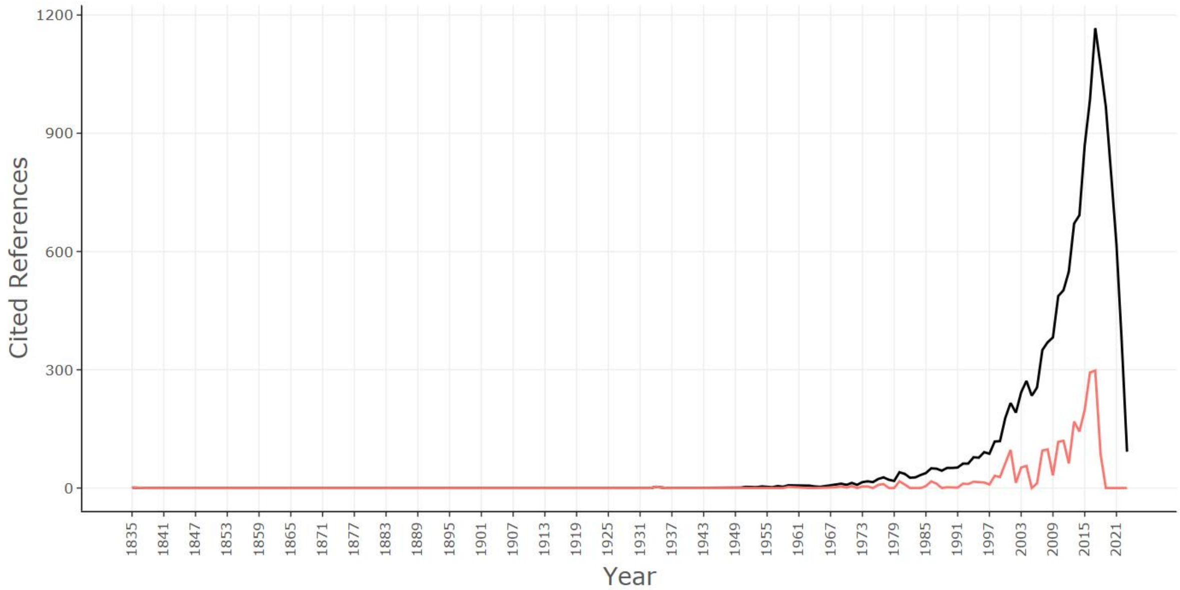

Figure 15. Emoticons and Emojis in Consumer Behavior RPYS (1880–2023)

Table 4. RPYS Main Peaks in Emoticons and Emojis in Consumer Behavior Research

Year	Citations	5-year median deviation	Document
2000	178	60	Wolf (2000)
2001	216	97	Walther and D'Addario (2001)
2003	243	52	Keller (2003)
2004	272	56	Hennig-Thurau, Gwinner, Walsh, and Gremler (2004)
2007	350	95	P. Schultz,Nolan, Cialdini, Goldstein, and Griskevicius (2007)
2008	370	98	Derks, Bos, and von Grumbkow (2008)
2010	487	117	Thelwall, Buckley, Paltoglou, Cai, and Kappas (2010)
2011	502	120	F. Schultz,Utz, and Goritz (2011)
2012	549	62	Ganster et al. (2012)
2015	869	198	Kralj Novak, Smailović, Sluban, and Mozetič (2015)
2016	985	293	Kaye,Wall, and Malone (2016)
2017	1167	298	Gallo, Swaney-Steuve, and Chambers (2017)

The table shows that the peaks occurred from 2000 to 2017. The first peak occurred in 2000 and coincided with the publication of Wolf's (2000) seminal work examining gender differences in using emoticons in newsgroups. In this article, the author found that while women tend to use emoticons humorously, most emoticons used by men tend to be sarcastic. The second peak coincided with the publication of Walther and

D'Addario's (2001) article which designed an experiment aimed to examine the impact of emoticons on message interpretation. The authors found that "emoticons' contributions were outweighed by verbal content, but a negativity effect appeared such that any negative message aspect—verbal or graphic—shifts message interpretation in the direction of the negative element" (p. 324). The third peak occurred in 2003 with the publication of Keller's (2003) article synthesizing multidimensional brand knowledge. In this article, the author argued that adopting a broader and more holistic approach is needed to advance branding theory and practice. The fourth peak occurred in 2004 with the publication of Hennig-Thurau et al.'s (2004) article investigating factors leading to electronic word of mouth (eWOM) behavior. Results showed that consumers engage on eWOM mainly to fulfill their desires for social interaction and to gain economic incentives. The fifth peak coincided with the publication of P. Schultz et al.'s article (2007) examining the role of normative messages in promoting household energy conservation. The sixth peak occurred in 2004 with the publication of Derks et al.'s (2008) article examining the influence of emoticons on message interpretation. Results showed that emoticons can be used to convey the same functions as nonverbal behavior. The seventh peak coincided with the publication of Thelwall et al.'s article (2010) developing a new algorithm that can be used to detect sentiment in informal short texts. The eighth peak coincided with the publication of F. Schultz et al.'s (2011) article examining crisis communication via social media. The ninth peak occurred with the publication of Ganster et al.'s (2012) article examining emoticons' differential effects on a recipient's mood. The tenth peak occurred with the publication of Novak et al.'s (2015) article developing the first emoji sentiment lexicon. The eleventh peak occurred with the publication of Kay et al.'s (2016) article examining emoticons' impact on the recipient across several products. The final peak occurred in 2017 with Gallo et al.'s (2017) article examining how children use emotional words and emojis in food-related products.

DISCUSSION AND CONCLUSION

The major aim of this study was to investigate the evolution of emoticons and emojis in consumer behavior research over the last two decades. To do so, bibliometric techniques were used to analyze 261 emoticons and emojis research documents written by 762 authors. Because "an arbitrary selection of evidence is often not fully representative of the state of existing knowledge, and the selection of some studies over others ultimately leads to what is known in statistical analysis as a sample selection bias", the author aimed to analyze all the Scopus-indexed documents dealing with the emoticons and emojis in consumer behavior. It is argued that this is the first study to map the landscape of emoticons and emojis in consumer behavior research. The author also argue that this research is timely since there has been tremendous growth in this domain over the last two decades. Furthermore, it is resorted to SNA techniques to produce a complete picture of the dynamic interconnectedness of emoticons and emojis in consumer behavior research. C. Chen and Leydesdorff (2014) noted that SNA techniques can be used to trace and chart shifting paradigms in specific scientific research over time.

By merging bibliometric and SNA techniques, the author detected the knowledge structure of emoticons and emojis in consumer behavior research and its interconnected collaborative networks. For example, by examining how authors collaborate in the field, the author revealed a sparse "hub-and-spoke" network structure. This structure is consistent with the well-known "small world" network literature (Milgram, 1967). This finding is significant because it shows that only a handful of authors dominate the emoticons and emojis in consumer behavior research. S. Park, Lim, and Park (2015) labeled such authors "information brokers" because they are instrumental in forming bridges through which information is diffused across the network effectively (N. Smith & Graham, 2019; Shirky, 2008). The results also show that all emoticons and emojis research networks reveal a "Matthew Effect" or "preferential attachment", a paradigm in which a certain network is only dominated by a few hubs (Newman & Girvan, 2004; Himelboim, Smith, & Shneiderman, 2013; Vanni et al., 2014).

LIMITATIONS AND FUTURE RESEARCH

Like any other study, this research has its limitations. First, the results reported here are based on one database, namely the Scopus database. Thus, the results must be interpreted with caution as a selection bias might have occurred. To examine the robustness of this research findings, future research might merge Scopus with other databases such as PubMed or WoS (C. Neuhaus, Neuhaus, Asher, & Wrede, 2006). Second, the author has focused solely on emoticons and emojis research documents written in English. Thus, the coverage might be limited (Qian et al., 2019). Consequently, future research might expand on this by adding emoticons and emojis in research published in other languages. Third, although the author has analyzed the whole domain of emoticons and emojis in consumer behavior research, future studies may focus on specific journals publishing such research like *Food Quality and Preference, Food Research International, Journal of Sensory Studies, Frontiers in Psychology,* and *Computers in Human Behavior* among others.

REFERENCES

Arya, V., Sethi, D., & Verma, H. (2018). Are emojis fascinating brand value more than textual language? Mediating role of brand communications to SNS and brand attachment: An insight from India. *Corporate Communications*, *23*, 648-670.

Ávila-Robinson, A., & Wakabayashi, N. (2018). Changes in the structures and directions of destination management and marketing research: A bibliometric mapping study, 2005–2016, *Journal of Destination Marketing & Management*, *10*, 101-111.

Baek, T., Kim, S., Yoon, S., Choi, Y., Choi, D., & Bang, H. (2022). Emojis and assertive environmental messages in social media campaigns. *Internet Research*, *32*, 988-1002.

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

Banckendorff, P. (2009). Themes and trends in Australian and New Zealand tourism research: A social network analysis of citations in two leading journals (1994–2007). *Journal of Hospitality and Tourism Management, 16*, 1-15.

Beattie, A., Edwards, A., & Edwards, C. (2020). A bot and a smile: Interpersonal impressions of chatbots and humans using emoji in computer-mediated communication. *Communication Studies*, *71*, 409-427.

Buchholz, K. (2024). In 2025, Global Emoji Count Could Grow to 3,790. Retrieved from https://www.statista.com/chart/17275/number-of-emojis-from-1995-bis-2019/

Callon, M., Courtial, J., & Laville, F. (1991). Co-word analysis as a tool for describing the network of interactions between basic and technological research: The case of polymer chemistry. *Scientometrics*, *22*, 155-205.

Casado-Molina, A., Rojas de Garcia, M., Alarcon-Urbistondo, P., & Romero-Charneco, M. (2022). Exploring the opportunities of the emojis in brand communication: The case of the bear industry. *International Journal of Business Communications*, *59*, 315-333.

Chen, C., & Leydesdorff, L. (2014). Patterns of connections and movements in dual-map overlays: A new method of publication portfolio analysis. *Journal of the Association for Information Science and Technology*, *65*, 334-351.

Chen, C., Song, I., Yuan, X., & Zhang, J. (2008). The thematic and citation landscape of data and knowledge engineering (1985–2007). *Data & Knowledge Engineering*, *67*, 234-250.

Chen, X., & Liu, Y. (2020). Visualization analysis of high-speed railway research based on CiteSpace. *Transport Policy*, *85*, 1-17.

Chew, C., & Eysenbach, G. (2010). Pandemics in the age of Twitter: Content analysis of Tweets during the 2009 H1N1 outbreak. *PLoS ONE*, *5*(11), e14118.

Cini, C. (2022). How emojis became a political language of symbols. Retrieved from https://www.lemonde.fr/en/pixels/article/2022/12/03/howe-emojis-became-a-political-language-of-symbols_6006472_13.html

Cobo, M., Lopez-Herrera, A., Herrera-Viedma, E., & Herrera, F. (2011). An approach for detecting, quantifying, and visualizing the evolution of a research field: A practical application to the fuzzy sets theory field. *Journal of Informetrics*, *5*, 146-166.

Corbet, S., Dowling, M., Gao, X., Huang, S., Lucey, B., & Vigne, S. (2019). An analysis of the intellectual structure of research on financial economics of precious metals. *Resources Policy*, *63*, 101416.

Coyle, M., & Carmichael, C. (2019). Perceived responsiveness in text messaging: The role of emoji use. *Computers in Human Behavior*, *99*, 181-189.

Cramer, H., De Juan, P., & Tetreault, J. (2016, September). Sender-intended functions of emojis in US messaging. In *Proceedings of the 18th international conference on human-computer interaction with mobile devices and services* (pp. 504-509). https://doi.org/10.1145/2935334.2935370

Daniel, T., & Camp, A. (2020). Emojis affect processing fluency on social media. *Psychology of Popular Media Culture*, *9*, 208-213.

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

Derks, D., Bos, A., & von Grumbkow, J. (2008). Emoticons and online message interpretation. *Social Science Computer Review*, *26*, 379-388.

Ding, Y. (2011). Scientific collaboration and endorsement: Network analysis of co-authorship and citation networks. *Journal of Informetrics*, *5*, 187-203.

Elango, B., & Rajendran, P. (2012). Authorship trends and collaboration pattern in the marine sciences literature: A scientometric study. *International Journal of Information Dissemination and Technology*, *2*, 166-169.

Evans, V. (2015). No, the rise of the emoji doesn't spell the end of language. Retrieved from https://www.bangor.ac.uk/news/archive/no-the-rise-of-the-emoji-doesn-t-spell-the-end-of-language-22914

Fang, S., Wei, Y., & Wang, S. (2023). 30 years of exchange rate analysis and forecasting: A bibliometric review. *Journal of Economic Surveys*, 1-35.

Firdaus, A., Ab Razak, M., Feizollah, A., Hashem, I., Hazim, M., & Anuar, N. (2019). The rise of "blockchain": Bibliometric analysis of blockchain study. *Scientometrics*, *120*, 1289-1331.

Fomina, Y., Glinska-Newes, A., & Ignasiak-Szulc, A. (2022). Community supported agriculture: Setting the research agenda through a bibliometric analysis. *Journal of Rural Studies*, *92*, 294-305.

Gallo, K., Swaney-Steuve, M., & Chambers, D. (2017). A focus group approach to understanding food-related emotions with children using words and emojis. *Journal of Sensory Studies*, *32*, e12264.

Ganster, T., Eimler, S., & Kramer, N. (2012). Same same but different? The differential influence of smiles and emoticons on person perception. *Cyberpsychology, Behavior, and Social Networking*, *15*, 226-230.

Gibson, W., Huang, P., & Yu, Q. (2018). Emoji and communicative action: The semiotics, sequence and gestural actions of "face covering hand". *Discource, Context & Media*, *26*, 91-99.

Glänzel, W., & Schubert, A. (2004). Analysing scientific networks through co-authorship. In H. Moed, W. Glanzel, & U. Schmoch (Eds.), *Handbook of quantitative science and technology research: The use of publication and patent statistics in studies of S&T systems* (pp. 257-276). Dordrecht, Netherlands: Springer.

Gonzales-Valiente, C. (2019). Redes de citación de revistas iberoamericanas de bibliotecología y ciencia de la información en Scopus. *Bibliotecas Anales de Investigación*, *15*, 83-98.

Hennig-Thurau, T., Gwinner, K., Walsh, G., & Gremler, D. (2004). Electronic word-of-mouth via consumer-opinion platforms: What motivates consumers to articulate themselves on the Internet?. *Journal of Interactive Marketing*, *18*, 38-52.

Himelboim, I., Smith, M., & Shneiderman, B. (2013). Tweeting apart: Applying network analysis to detect selective exposure clusters in Twitter. *Communication Methods and Measures*, *7*, 195-223.

Hsu, L., & Chen, Y. (2020). Neuromarketing, subliminal advertising, and hotel selection: An EEG study. *Australasian Marketing Journal*, *28*, 200-208.

Jaeger, S. R., Lee, S. M., Kim, K. O., Chheang, S. L., Jin, D., & Ares, G. (2017). Measurement of product emotions using emoji surveys: Case studies with tasted foods and beverages. *Food Quality and Preference, 62*, 46–59.

Jiang, Y., Ritchie, B., & Benckendorff, P. (2019). Bibliometric visualization: An application to tourism crisis and disaster research: *Current Issues in Tourism*, *22*, 1925-1957.

Kaye, L., Wall., L., & Malone, S. (2016). Turn that frown upside-down: A contextual account of emoticon usage on different virtual platforms. *Computers in Human Behavior*, *60*, 463-467.

Keller, K. (2003). Brand synthesis: The multidimensionality of brand knowledge. *Journal of Consumer Research*, *29*, 595-600.

Kessler, K. (1963). Bibliographic coupling between scientific papers. *Journal of the Association for Information Science and Technology*, *14*, 10-25.

Khan, G., & Wood, J. (2016). Knowledge networks of the information technology management domain: A social network analysis approach. *Communications of the Association for Information Systems*, *39*, 367-397.

Knoke, D., & Yang, S. (2010). *Social Network Analysis*. Los Angeles, CA: Sage.

Kralj Novak, P., Smailović, J., Sluban, B., & Mozetič, I. (2015). Sentiment of emojis. *PLoS ONE*, *10*(12), e0144296.

Law, J., Bauin, S., Courtial, J., & Wittaker, J. (1988). Policy and the mapping of scientific change: A co-word analysis of research into environmental acidification. *Scientometrics*, *14*, 251-264.

Lefebvre, S., Boman, L., & Orlowski, M. (2024). Look on the bright side: Emojis impact tipping behavior. *International Journal of Hospitality Management*, *117*, 103653.

Li, X., Chan, K., & Kim, S. (2019). Service with emoticons: How customers interpret employee use of emoticons in online service encounters. *Journal of Consumer Research*, *45*, 973-987.

Li, Y., & Shin, H. (2023). Should a luxury brand's chatbot use emoticons? Impact on brand status. *Journal of Consumer Behavior*, *22*, 569-581.

Liao, H., Tang, M., Li, Z., & Lev, B. (2019). Bibliometric analysis for highly cited papers in operations research and management science from 2008 to 2017 based on essential science indicators. *Omega*, *88*, 228-236.

Liu, D., Lv, Y., & Huang, W. (2023). How do consumers react to chatbots' humorous emojis in service failures. *Technology in Society*, *73*, 102244.

Lohmann, K., Pyka, S., & Zanger, C. (2017). The effects of smileys or receivers' emotions. *Journal of Consumer Marketing*, *34*, 489-495.

Lu, X., Ai, W., Liu, X., Li, Q., Wang, N., Huang, G., & Mei, Q. (2016). Learning from the ubiquitous language: An empirical analysis of emoji usage of smartphone users. In *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing* (pp. 770-780). New York, NY: ACM Press.

Ma, R., & Wang, W. (2021). Smile or pity? Examine the impact of emoticon valence on customer satisfaction and purchase intention. *Journal of Business Research*, *134*, 443-456.

Marx, W., Haunschild, R., Thor, A., & Bornmann, L. (2017). Which works are cited most frequently in climate change research literature? A bibliometric approach based on reference publication year spectroscopy. *Scientometrics*, *110*, 335-353.

McPherson, M., Smith-Lovin, L., & Cook, J. (2001). Birds of feather: Homophily in social networks. *Annual Review of Sociology*, *27*, 415-444.

McShane, L., Pancer, E., Poole, M., & Deng, Q. (2021). Emoji, playfulness, and brand engagement on Twitter. *Journal of Interactive Marketing*, *53*, 96-110.

Milgram, S. (1967). The small-world problem. *Psychology Today*, *2*, 60-67.

Moussa, S. (2019). An emoji-based metric for monitoring consumers' emotions toward brands on social media. *Marketing Intelligence and Planning*, *37*, 211-225.

Neff, M., & Corley, E. (2009). 35 years and 160,000 articles: A bibliometric exploration of the evolution of ecology. *Scientometrics*, *80*, 657-682.

Neuhaus, C., Neuhaus, E., Asher, A., & Wrede, C. (2006). The depth and breadth of Google Scholar: An empirical study. *Libraries and the Academy*, *6*, 127-141.

Newman, M., & Girvan, M. (2004). Finding and evaluating community structure in networks. *Physical Review E*, *69*, 1-15.

Park, S., Lim, Y., & Park, H. (2015). Comparing Twitter and YouTube networks in information diffusion: The case of the "Occupy Wall Street" movement. *Technological Forecasting & Social Change*, *95*, 208-217.

Prada, M., Rodrigues, D., Garrido, M., Lopes, D., Cavalheiro, B., & Gaspar, R. (2018). Motives, frequency and attitudes toward emoji and emoticon use. *Telematics and Informatics*, *35*, 1925-1934.

Qian, J., Law, R., & Wei, J. (2019). Knowledge mapping in travel website studies: A scientometric review. *Scandinavian Journal of Hospitality and Tourism*, *19*, 192-209.

Rodrigues, D., Prada, M., Gspar, R., Garrido, M., & Lopes, D. (2018). Lisbon emoji end emoticon database (LEED): Norms for emoji and emoticons in seven evaluative dimensions. *Behavior Research Methods*, *50*, 392-405.

Sadeghi-Niaraki, A. (2023). Internet of Things (IoT) review of review: Bibliometric overview since its foundation. *Future Generation Computer Systems*, *143*, 361-377.

Schouteten, J. J., Verwaeren, J., Almli, V., & Rini, L. (2022). Comparing a product-specific versus a general emoji list to measure consumers' emotional associations with chocolate and predict food choice. *Food Research International*, *157*, 86-97.

Schouteten, J., Verwaeren, J., Gellynck, X., & Almli, V. (2019). Comparing a standard to a product-specific emoji list for evaluating food products by children. *Food Quality and Preference*, *72*, 86-97.

Schultz, F., Utz, S., & Goritz, A. (2011). Is the medium the message? Perceptions of and reactions to crisis communication via Twitter, blogs and traditional media. *Public Relations Review*, *37*, 20-27.

Schultz, P., Nolan, J., Cialdini, R., Goldstein, N., & Griskevicius, V. (2007). The constructive, destructive, and reconstructive power of social norms. Psychological Science, *18*, 429-434.

Shirky, C. (2008). *The power of organizing without organizations*. New York, NY: Penguin Press.

Skovholt, K., Gronning, A., & Kankaanranta, A. (2014). The communicative function of emoticons in workplace e-mails. *Journal of Computer-Mediated Communication*, *19*, 780-797.

Smith, L., & Rose, R. (2020). Service with a smiley face: Emojional contagion in digitally mediated relationships. *International Journal of Research in Marketing*, *37*, 301-319.

Smith, N., & Graham, T. (2019). Mapping the anti-vaccination movement on Facebook. *Information, Communication & Society*, *22*, 1310-1327.

The R Core Team. (2023). R: A language and environment for statistical computing (Version 3.3.1). Retrieved from https://web.mit.edu/r_v3.3.1/fullrefman.pdf

Thelwall, M., Buckley, K., Paltoglou, G., Cai, D., & Kappas, A. (2010). Sentiment strength detection in short informal text. *Journal of the American Society for Information Science and Technology*, *61*, 2544-2558.

Thor, A., Bornmann, L., Marx, W., & Mutz, R. (2018). Identifying single influential publications in a research field: New analysis opportunities of the CRExplorer. *Scientometrics*, *116*, 591-608.

Thor, A., Marx, W., Leydesdorff, L., & Bornmann, L. (2016). Introducing CitedReferenceExplorer (CRExplorer): A program for reference publication year spectroscopy with cited references standardization. *Journal of Informetrics*, *10*, 508-515.

van Eck, N., & Waltman, L. (2014). CitNetExplorer: A new software tool for analyzing and visualizing citation networks. *Journal of Informetrics*, *8*, 802-823.

van Eck, N., & Waltman, L. (2019). VOSviewer Manual: Manual for VOSviewer version 1 .6.13. Retrieved from https://www.vosviewer.com/documentation/Manual_VOSviewer_1.6.13.pdf

Vanni, T., Mesa-Frias, M., Sanchez-Garcia, R., Roesler, R., Schwartsmann, G., Goldani, M. Z., & Foss, A. M. (2014). International scientific collaboration in HIV and HPV: Anetwork analysis. *PLoS ONE*, *9*(3), e93376.

Vidal., L., Ares, G., & Jaeger, S. (2016). Use of emoticons and emoji in tweets for food-related emotional expression. *Food Quality and Preference*, *49*, 119-128.

Volker, J., & Mannheim, C. (2021). Turned in on senders' self-revelation: Emojis and emotional intelligence influence interpretation of WhatsApp messages. *Computers in Human Behavior Reports*, *3*, 100062.

Walther, J. B., & D'Addario, K. P. (2001). The impacts of emoticons on message interpretation in computer-mediated communication. *Social Science Computer Review*, *19*, 324-347.

Wei, Y., Wang, J., Chen, T., Yu, B., & Liao, H. (2018). Frontiers of low-carbon technologies: Results from bibliographic coupling with sliding window. *Journal of Cleaner Production*, *190*, 422-431.

Wider, W., Gao, Y., Chan, C., Lin, J., Li, J., Tanucan, J., & Fauzi, M. (2023). Unveiling trends in digital tourism research: A bibliometric analysis of co-citation and co-word analysis. *Environmental and Sustainability Indicators*, *20*, 100308.

Wolf, A. (2000). Emotional expression online: Gender differences in emoticon use. *CyberPsychology & Behavior*, *3*, 827-833.

Zhu, J., & Hua, W. (2017). Visualizing the knowledge domain of sustainable development research between 1987 and 2015: A bibliometric analysis. *Scientometrics*, *110*, 893-914.

Zou, X., Yue, W., & Vu, H. (2018). Visualization and analysis of mapping knowledge domain of road safety. *Accident Analysis and Prevention*, *118*, 131-145.