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Doctoral Dissertation

MOBILE SOCIAL MEDIA AND SOCIAL MEDIA: ADVANCING
OUR UNDERSTANDING OF VALUE CREATION, USE
BEHAVIOR, AND COMPETITIVE INTELLIGENCE

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ABSTRACT

The combination of social media and mobile technology has revolutionized the ways customers and firms create value. The purpose of this thesis is to better understand the role of mobile social media and social media in value creation. The thesis comprises three chapters. The first chapter provides a systematic literature review about mobile social media and value creation to illustrate how firms and customers apply mobile social media to create and co-create value. The second chapter focuses on individuals' mobile social media use behavior. The study firstly examines the determinants that drive individuals to use mobile social media. Furthermore, the study detects unobserved heterogeneity among individual users and includes an international microsegmentation based on individuals' behavioral patterns. The third chapter aims to investigate how the gained competitive intelligence from social media data can be used to predict customer engagement and support decisions.

To achieve the purpose of the thesis, I applied different research methods in the three chapters. In the first chapter, the literature was collected using academic databases and manual cross-referencing. Then, the thematic analysis method was used to extract the specific value creation and exchange paths between firms and customers. In the second chapter, I proposed a model that integrated the technology acceptance model, motivation theory, and social influence theory to explore the determinants of individuals' mobile social media use behavior. The data was collected using the survey method in China and the United States. For the data analysis, I firstly applied Partial Least Squares Structural Equation Modeling (PLS-SEM) to estimate the correlations amongst variables. Then, I applied the REBUS-PLS algorithm to detect the unobserved heterogeneity and conduct the *post hoc* segmentation. As for the third chapter, I

extended the existing social media competitive intelligence frameworks by integrating the influence of the external environment and the phase to predict customer engagement. I conducted a case study to illustrate how to implement the framework. I collected tweets generated by the leading American catering brands using Application Programming Interface (API) before and during the COVID-19 pandemic. In the first phase, I used Amazon comprehend and Latent Dirichlet allocation (LDA) to analyze sentiments and topics behind the unstructured text data. In the second phase, I trained the classifiers using six machine learning algorithms to predict customer engagement behaviors in social media.

The findings of the three chapters reveal that mobile and social media are effective value creation tools in modern marketing. Firms that conduct business through mobile social media can apply digital technology to create value for customers. They can also capture value from customers in return. Besides, customers co-create value for firms. Mobile social media use behavior is a premise in value creation. Specifically, individuals' attitude towards the applications is a key factor that bridges the motivational and social factors and actual use behavior. At the same time, global mobile social media users are not homogeneous. They can be segmented into different groups which are significantly different in terms of their behavioral patterns, cultural values, and demographic characteristics. Apart from that, firms can also make use of competitive intelligence extracted from social media data to predict customer engagement behaviors and support decisions under different environments. The results show that the neutral sentiment predominates in the firm-generated content, and the number of topics raises in the pandemic situation. Moreover, the influence of the predictors on customer engagement is different before and during the pandemic.

This thesis makes several contributions to the social media literature. First, after summarizing current knowledge on mobile social media, the thesis provides a conceptual framework on value creation in mobile social media and presents a list of future research guidelines. Second, the thesis deepens our understanding of mobile social media use behavior at the individual level by demonstrating that motivation theory has more explanatory power than social influence theory. In addition, by detecting the unobserved heterogeneity in mobile social media users, the thesis highlights the importance of incorporating international microsegmentation in marketing strategy. Third, the thesis also highlights the roles of social media data and firms in value creation. By proposing a refined social media competitive intelligence framework, the thesis demonstrates that competitive intelligence gained from social media data empowers customer engagement prediction and decision support, especially during times of high environmental uncertainty.

RESUMEN

La combinación de redes sociales y tecnología móvil ha revolucionado la forma que los clientes y las empresas crean valor. El objetivo de esta tesis es comprender mejor el papel de las redes sociales móviles y las redes sociales en la creación de valor. La tesis consta de tres artículos. El primer estudio proporciona una revisión de literatura sistemática sobre las redes sociales móviles y la creación de valor, que ilustra cómo las empresas y los clientes aplican las redes sociales móviles para crear y co-crear valor. El segundo artículo se centra en el comportamiento de uso de las redes sociales móviles. Por un lado, el estudio examina los factores determinantes que impulsan a los individuos a utilizar las redes sociales móviles. Por otro lado, el estudio detecta la heterogeneidad no observada entre los usuarios individuales e incluye una microsegmentación internacional basada en patrones de comportamiento de los individuos. El tercer artículo tiene el objetivo de investigar cómo se utiliza la inteligencia competitiva obtenida de los datos de las redes sociales para predecir el compromiso del cliente y apoyar la toma de decisiones.

Para cumplir el propósito de la tesis, apliqué diferentes métodos de investigación en los tres artículos. En el primer artículo, recopilé la literatura utilizando bases de datos académicas y las referencias de los artículos localizados. Luego, utilicé el método de análisis temático para extraer las rutas específicas de creación de valor e intercambio entre empresas y clientes. En el segundo artículo, propuse un modelo que integraba el modelo de aceptación de la tecnología, la teoría de la motivación y la teoría de la influencia social para explorar los determinantes del comportamiento de uso de las redes sociales móviles. Recogí los datos mediante encuestas en China y Estados Unidos. Para el análisis de datos, en primer lugar, apliqué *Partial Least Squares*

Structural Equation Modeling (PLS-SEM) para estimar las correlaciones entre las variables. Luego, apliqué el algoritmo REBUS-PLS para detectar la heterogeneidad no observada y realizar la segmentación *post hoc*. En cuanto al tercer artículo, amplié los marcos de inteligencia competitiva de las redes sociales existentes al integrar la influencia del entorno externo y proponer una nueva fase que predice el compromiso del cliente. Realicé un estudio de casos para ilustrar cómo implementar el marco. Recogí tweets generados por las principales marcas de hostelería estadounidenses utilizando el *Application Programming Interface* (API) antes y durante la pandemia de COVID-19. En la primera fase, utilicé el *Amazon Comprehend* y el *Latent Dirichlet Allocation* (LDA) para analizar los sentimientos y los temas detrás de los datos textuales no estructurados. En la segunda fase, entrené los clasificadores utilizando seis algoritmos de aprendizaje automático para predecir los comportamientos de compromiso del cliente en las redes sociales.

Los hallazgos de los tres artículos revelan que los dispositivos móviles y las redes sociales son herramientas efectivas de creación de valores en el marketing moderno. Las empresas que realizan negocios a través de las redes sociales móviles pueden aplicar la tecnología digital para crear valor para los clientes. También pueden capturar valor de los clientes a cambio. Además, los clientes co-crean valor para las empresas. El comportamiento de uso de las redes sociales móviles es una premisa en la creación de valor. Específicamente, la actitud de los individuos hacia las aplicaciones es un factor clave que une los factores motivacionales y sociales y el comportamiento de uso real. Al mismo tiempo, los usuarios de redes sociales móviles globales no son homogéneos. Pueden segmentarse en diferentes grupos que son significativamente diferentes en términos de sus patrones de comportamiento, valores culturales y características

demográficas. Además, las empresas también pueden hacer uso de la inteligencia competitiva extraída de los datos de las redes sociales para predecir los comportamientos de compromiso del cliente y apoyar la toma de decisiones en diferentes entornos. Los resultados muestran que el sentimiento neutral predomina en el contenido generado por la empresa, y el número de temas aumenta en la situación de pandemia. Además, la influencia de los predictores en el compromiso del cliente es diferente antes y durante la pandemia.

Esta tesis realiza varias contribuciones a la literatura sobre redes sociales. En primer lugar, tras resumir los conocimientos actuales sobre las redes sociales móviles, la tesis proporciona un marco conceptual sobre la creación de valor en las redes sociales móviles y presenta una lista de las pautas de investigación futuras. En segundo lugar, la tesis profundiza nuestra comprensión del comportamiento de uso de las redes sociales móviles a nivel individual al demostrar que la teoría de la motivación tiene más poder explicativo que la teoría de la influencia social. Aparte de esto, al detectar la heterogeneidad no observada en los usuarios de redes sociales móviles, la tesis destaca la importancia de incorporar la microsegmentación internacional en la estrategia de marketing. En tercer lugar, la tesis también destaca el papel de las empresas y de los datos de las redes sociales en la creación de valor. Al proponer un marco refinado de inteligencia competitiva en redes sociales, la tesis demuestra que la inteligencia competitiva obtenida de los datos de las redes sociales potencia la predicción del compromiso del cliente y el apoyo a la toma de decisiones, especialmente en tiempos de alta incertidumbre en el entorno.

GENERAL INTRODUCTION

1. Digital marketing and social media

Digital marketing can be viewed as an adaptive process facilitated by technologies in which firms collaborate with customers and partners to jointly create, communicate, deliver, and sustain value for all stakeholders (Kannan & Li, 2017). Digital marketing has changed customer behavior and the way firms conduct business (Dwivedi et al., 2021). At the customer level, digital marketing stimulates the creation of more informed, empowered, and connected groups of customers in both the real and virtual worlds (Krishen et al., 2021). At the firm level, the contribution of digital marketing is not limited to the content of the message but offers opportunities for firms to engage and establish a direct dialogue with customers, build, consolidate, and maintain brand awareness, gather market knowledge and customer feedback, and make the right decisions in the marketplace (Tiago & Veríssimo, 2014).

Social media is one of the digital areas that firms primarily invest in (Tiago & Veríssimo, 2014). Social media is defined as *“a group of internet-based applications that build on the ideological and technological foundations of Web 2.0, and that allow the creation and exchange of User Generated Content”* (Kaplan & Haenlein, 2010, p. 61). In January 2021, there were 4.2 billion active social media users around the world, and 98.8% of them accessed social media applications through mobile devices (We are social & Hootsuite, 2021). In recent years, firms have been actively using social media to increase brand awareness, engage the community, and grow their audiences (Statista, 2021). Social media is influencing customers' purchase decisions: In the United States, 51% of the customers' decisions are influenced by social media advertising (Statista, 2021).

Social media are two-way communication platforms, which are more cost-effective than traditional media (Kaplan, 2012). Meanwhile, social media has the ability to cross boundaries of distance and time, which extends the scope of research of digital marketing (Krishen et al., 2021). Social media applications can be accessed from both websites as well as mobile devices. Mobile devices offer users different experiences since they can access social media applications any time and everywhere, stay connected with the world, exchange different types of information for personal specific purposes, and develop multichannel relationships with customers (Larivière et al., 2013). Mobile technologies distinguish mobile social media from social media in two aspects: location-sensitivity and time-sensitivity (Kaplan, 2012). While location-sensitivity refers to whether users' exact location can be identified in the messages on mobile social media, time-sensitivity refers to whether the messages can be transmitted instantaneously or with a time delay (Kaplan, 2012).

The literature reveals that digital marketing and social media are meaningful research areas. Järvinen et al. (2012) suggested that digital marketing and social media create awareness, enhance brand image, and serve to acquire new customers. Tiago and Veríssimo (2014) revealed that digital media helps information gathering, improves feedback, increases knowledge and productivity, enhances the external relationship, supports the decision-making process, and better measures outcomes. Kannan and Li (2017) emphasized that digital technologies like social media and mobile devices build foundational capabilities to create value jointly for customers as well as for firms themselves that shape firms' actions and strategies and have an impact on the process of value creation. Later, Herhausen et al. (2020) discussed the digital marketing capabilities that are specific to social media, highlighting that social media serve as

a marketing tool and resources that are widely used in industrial firms at either the employee or the organizational level.

2. Value creation in mobile and social media

Marketing is a process in which firms create value for customers and build strong customer relationships in order to capture value from customers in return (Kotler & Armstrong, 2020). Value can be generally defined as the trade-off between the benefits (“what you get”) and the sacrifices (“what you give”) in a market exchange (Ulaga, 2003; Zeithaml, 1988). The creation of value is paramount to firms’ survival (Tzokas & Saren, 1999). Social media and mobile technologies are important value creation tools (Agnihotri, 2020; Larivière et al., 2013). On the one hand, the applications and functions designed and developed by firms enrich customers’ experience and make their daily life more convenient (Huang et al., 2019). On the other hand, the explosive growth of media, digital devices, and software applications provides firms with unprecedented opportunities to leverage social media data to create greater value to customers and enhance their experiences, satisfaction, and loyalty (Michel Wedel & Kannan, 2016).

The current literature has discussed the importance of social media and mobile technologies in marketing research. Kaplan and Haenlein (2010), in a pioneer study, provided a definition and classification of social media applications and offered advice for firms that decide to use social media. In another study, Kaplan (2012) introduced the concept of mobile social media and its differences with social media and discussed how firms could make use of mobile social media for marketing research. Later, Ketonen-Oksi et al. (2016) discussed how value is created in social media networks and the impact of social media on present and future

business models. Lamberton and Stephen (2016) analyzed the major trends of three research fields, including digital marketing, social media marketing, and mobile marketing, revealing their relationships with value creation. Focusing on digital marketing, Kannan and Li (2017) developed a framework in which they highlighted the touchpoints in the marketing process as well as in the marketing strategy process where digital technologies have an impact. However, knowledge on how social media and mobile technology can be used to create value is still scarce (Grönroos & Ravald, 2011). In particular, the roles of firms, customers, social media, and mobile technology in the value creation process are ambiguous.

Firms and customers are two important value creators in the process of value creation. Value creation at the firm level is related to firms' activities (Amit & Zott, 2001) which enable firms to build relationships with their customers (Tzokas & Saren, 1999). Firms' value creation activities start from providing customers with products and services, which is a prerequisite in the value creation process (Grönroos & Voima, 2013). Firms can also generate brand-related content (Akhtar et al., 2019; Bu et al., 2020) and interact with customers (Chae & Ko, 2016). Such activities enable firms to gain customer satisfaction (Zhao et al., 2016), customer loyalty (Hew et al., 2016), and customer equity (Kim et al., 2017).

Apart from that, firms can also extract knowledge from social media data generated by competitors and customers to acquire marketing insights and competitive intelligence (Bianchi & Andrews, 2015; Bolat et al., 2016). Analysis of data generated by firms in social media provides opportunities to identify industrial changes (Michel Wedel & Kannan, 2016), monitor competitors' strategies (Bose, 2008), and forecast the trend (Michel Wedel & Kannan, 2016). Moreover, data analysis on content generated by customers, such as valence and topics of

reviews, help firms to target customers' needs and preferences and optimize offerings (Ibrahim & Wang, 2019). Therefore, firms can make the right decisions and develop marketing strategies to keep their industrial competitive advantages (Keegan & Rowley, 2017).

Value creation at the customer level concentrates on customers' activities in social media. Customers' value creation activities start from using firm-provided products and services, such as social media applications. Moreover, customers can engage and interact with firms directly to provide innovative ideas to help firms to optimize their products and services (Nguyen et al., 2015; Presi et al., 2016). In these activities, customers are considered as value co-creators who co-produce resources and processes with the firm and co-create value jointly (Prahalad & Ramaswamy, 2004; Ramaswamy & Ozcan, 2016, 2018). Besides, customers can also share personal experiences to provide useful recommendations to other customers (Gummerus, 2013; Heinonen et al., 2010). Customers' online reviews are essential to firms' performance because of their positive impact on other customers' attitudes toward the brand (Vahdat et al., 2020), brand trust (Chae & Ko, 2016), and purchase intention (Kim et al., 2017; Sun et al., 2016).

3. International segmentation of social media users

Research on heterogeneity in the behaviors of individual consumers is a core premise on which marketing strategy is based (Michel Wedel & Kannan, 2016). However, globalization has made many firms recognize that the similarities of customers' attributes, needs, and behaviors in different countries have increased (Ter Hofstede et al., 1999; Wedel & Kamakura, 2002). In many industries, national borders are becoming less and less important as international

activities increase (Steenkamp & Hofstede, 2002). The concept of international segmentation has, therefore, gained more attention in both academia and industry (Wedel & Kamakura, 2002).

International segmentation is the process of dividing a market into distinct subsets of customers that have homogenous attributes, behave in the same way, or have similar needs (Hassan & Katsanis, 1992; Keegan, 2017). Firms benefit from international segmentation because it helps them to identify and group the similarities and differences of potential customers, address customers' specific needs, and target potential customers at the international-segment level (Steenkamp & Hofstede, 2002; Wedel & Kamakura, 2002). Thus, firms can determine the best positioning for their product offerings in their chosen target market and devise an appropriate marketing strategy (Keegan, 2017). However, scholars and international marketers face challenges of effectively dealing with the structure of heterogeneity in customers' needs and segmenting consumers across borders (Steenkamp & Hofstede, 2002). The reason is that the process of international segmentation involves obtaining multiple comparative information, including countries, industries, products, and consumers in a given market and the cultures of the markets (Papadopoulos & Martín Martín, 2011).

In the international segmentation literature, the country has been widely used as the aggregated unit of analysis in the segmentation process. Researchers have explored the international segments of consumers in both developed (Ruiz de Maya et al., 2011) and developing countries (Schlager & Maas, 2013). Countries can be characterized by macro factors that are assumed to be relevant to customers (Baalbaki & Malhotra, 1993). Also, countries can be characterized by aggregated consumer characteristics (Baalbaki & Malhotra, 1993). Taking the country as the unit of analysis, Gaston-Breton and Martín Martín (2011) proposed a two-

stage market selection and segmentation model that integrated market attractiveness (at the country level) and consumer value (at the consumer level) to help institutions and market-seeking multinational enterprises segment European macro-regions and groups of consumers.

The worldwide prevalence of mobile and social media adoption has provided opportunities for new research on international segmentation. According to a recent industrial report, there are 4.2 billion active social media users around the world, and 98.8% of them access social media platforms via mobile devices (We are social & Hootsuite, 2021). However, research on international segmentation in the mobile social media market is scarce, which hinders our understanding of global users' needs toward mobile social media. Existing studies have conducted cross-cultural analysis on mobile social media use behavior at the individual level to investigate the determinants that drive their use behavior (Hoehle et al., 2015). Among them, the country has been the most frequently used criterion for classifying users, and users in a country are typically assumed to display similar behavioral patterns and cultural values (Hoehle et al., 2015). However, in the age of globalization, the country has become a less important segmentation variable (Marreiros et al., 2020). *A priori* segmentation, which segments users based on predefined segmentation variables, such as nationality, may hide differences in consumer behavior if the heterogeneous behavioral patterns really exist (Michel Wedel & Kamakura, 2002). *Post hoc* segmentation, which segments respondents based on their data and the similarity of multivariate individual profiles (Kalafatis & Cheston, 1997), is a more suitable approach.

4. Social media data, competitive intelligence, and environmental uncertainty

Social media provides huge amounts of sources for textual data, which can be generated when firms and customers post, comment, or interact on social media platforms (Humphreys & Wang, 2018). Social media data has several characteristics. The data is generated by very large quantities and is dynamic (Stieglitz et al., 2014; Zeng et al., 2010). In addition, social media data is complex and generally involves both structured and unstructured nature (Stieglitz et al., 2014). Structured data, such as the number of likes, comments, and retweets, is predefined, numeric, unifacted, and non-concurrent that can be accessed and analyzed directly (Balducci & Marinova, 2018). On the contrary, unstructured data, such as reviews and tweets, is characterized as non-numeric, multifaceted, and concurrent representation, which needs to be converted into structured data before continuing more advanced data analysis (Balducci & Marinova, 2018).

Mining social media data provides opportunities for firms to gain competitive intelligence, which enhances sales performance (Itani et al., 2017). Text mining is a process that transforms unstructured data into a structured one, which facilitates knowledge extraction and targeted information delivering (Kumar et al., 2020). “*Competitive intelligence is a process involving the gathering, analyzing, and communicating of environmental information to assist in strategic decision making*” (Dishman & Calof, 2008, p. 767). Many firms are developing business analytic initiatives to extract intelligence from massive social media data (He et al., 2015), as this process generates business value (Erevelles et al., 2016). The knowledge extracted from competitors’ brand posts, such as topics, sentiments, and types of content, presents not only the current states of competitors (Berger et al., 2020) but also competitors’ strengths, weaknesses,

and marketing strategies (Bose, 2008). The knowledge also facilitates behavioral prediction (Moe et al., 2011), which provides guidance for decision support (Perez-Vega et al., 2021).

However, due to the characteristics of social media data, researchers face challenges in transforming knowledge obtained from social media data into meaningful outcomes (Lamberton & Stephen, 2016). The first challenge is the large amount of social media data (Schoen et al., 2013). Even though researchers have applied qualitative approaches to analyze the social media data (He et al., 2013; He, Shen, et al., 2015), it would be a daunting task to prepare and collect a large number of tweets manually or conduct the data analysis without using automated data analysis methods (Stieglitz et al., 2018). The second challenge is the growth of unstructured textual data. Many marketing applications require structuring this kind of data at scales non-accessible to human coding (Hartmann et al., 2019). Converting unstructured data into structured data is technically and algorithmically challenging (Baars & Kemper, 2008). It is hard to convert unstructured data (e.g., textual data) into structured data in the quantitative model (Lee & Bradlow, 2011). For the data to be useful, researchers need to consider how to measure, track, understand, and interpret the cause and consequences of marketplace behavior (Berger et al., 2020).

In response to the challenges posed by the characteristics of social media data, researchers have developed various social media competitive intelligence frameworks to illustrate how to extract intelligence from social media data. Topic modeling, sentiment analysis, and social network analysis are the main methods used to analyze social media content (He et al., 2013, 2016; He, Shen, et al., 2015; He, Wu, et al., 2015). The implementation of social media competitive intelligence frameworks results in numerous business benefits, such as making

sense during extreme events (Stieglitz et al., 2017) and improving decision making (He, Shen, et al., 2015). However, the value of social media competitive intelligence in marketing research has not been fully extracted.

In the first place, environmental uncertainty affects firms' decision-making and marketing strategies (Donthu & Gustafsson, 2020; Karpen & Conduit, 2020; Sharma et al., 2020). Firms' social media strategies may alter according to different environmental conditions. Yadav et al. (2021) found that sentiments and topics extracted from the Fortune CEOs' tweets changed before and during the COVID-19 pandemic. The COVID-19 pandemic, which is an infectious disease caused by a newly discovered coronavirus identified in Wuhan (China) since December 2019 (WHO, 2020), represents one of the most significant environmental changes in modern marketing history (He & Harris, 2020). Extracting competitive intelligence from social media data enables firms to know how competitors adapt their strategies to engage with customers during the crisis. However, the current social media competitive intelligence frameworks typically assume that firm-generated content as the data input in the framework is unchangeable. Thus, knowledge regarding the impact of the external environment on firms' social media strategies is still limited.

Second, competitive intelligence allows a company to predict what is going to happen in its competitive environment (Bose, 2008). Thus, predictive validity, i.e., the ability of the measured constructs to predict other constructs in the nomological network (Humphreys & Wang, 2018), is critically important in social media competitive intelligence frameworks. Influenced by environmental uncertainty, customers increasingly engage in social media during the pandemic (Donthu & Gustafsson, 2020). Customer engagement in social media can be

viewed as a non-transactional behavior toward a brand or firm that customers take on social media (van Doorn et al., 2010). Interactions between firms and customers can be valuable to predict their future relationships, which supports firms' marketing decisions (Perez-Vega et al., 2021), especially during an uncertain environment (Stieglitz et al., 2017). Firms are attempting to enhance customer engagement by leveraging social media competitive intelligence, as engaged customers are active participants (Shahbaznezhad et al., 2021) and value co-creators (Sashi, 2012; Wang & Kim, 2017). Moreover, these customers typically display greater brand loyalty (Algharabat et al., 2020; Kaur et al., 2020) and purchase intention (Meire et al., 2019). Therefore, customer engagement is one of the key drivers of a firm's financial success (Kunz et al., 2017). Nevertheless, existing social media competitive intelligence studies focus more on exploring the relationships between firm-generated content and customer engagement using descriptive analysis (Ibrahim et al., 2017; Yost et al., 2021). The effort of incorporating customer engagement prediction in the social media competitive intelligence framework is scarce. Therefore, knowledge on how to employ the gained intelligence to predict customer engagement in social media remains unclear.

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SCIENTIFIC REPORT

1. Research objectives

The first chapter aims to provide a systematic literature review on value creation in the mobile social media context. Specifically, the study identifies how firms and customers use mobile social media to create value and what are the specific value elements generated in the process of value creation. Further, the study provides an agenda for future research on mobile social media and value creation issues.

The second chapter is an empirical study that focuses on mobile social media adoption behavior at the individual level. To be specific, the study investigates the determinants of individuals' mobile social media use behavior and the international micro-segmentation in the mobile social media market. Regarding the determinants of mobile social media use behavior, the study examines how motivational factors and social influence factors affect individuals' actual use behavior through attitude towards mobile social media. With respect to international micro-segmentation, the study first explores the unobserved heterogeneity of global mobile social media users and then segments users based on their behavioral patterns.

The third chapter explores how competitive intelligence gained from social media data can be used to generate business value. Different from existing social media competitive intelligence frameworks, the study proposes a refined framework by incorporating the external environment to investigate the impact of the external environment on the firms' social media strategies. Besides, the study integrates the predictive phase into the framework to examine how the gained competitive intelligence from social media data empowers customer engagement prediction and decision support.

2. Contributions of the Ph.D. student

My contributions to the three studies have been total in terms of research opportunity identification, design, and execution. In the first chapter, I provided a systematic literature review on mobile social media and value creation, which contributes to mobile social media literature by illustrating an overall value creation process in a mobile social media context. By conducting a thematic analysis and a systematic review of mobile social media literature, I summarized current knowledge and proposed a conceptual framework to illustrate how firms and customers create value with each other by leveraging mobile social media applications. Apart from that, I also provided thirteen future research lines related to value creation in mobile social media by firms and customers from the perspectives of theory, method, and context.

The second chapter contributes to the mobile social media adoption and international microsegmentation literature. First, I identified different sets of factors that ultimately drive users' actual use behavior from multiple theoretical perspectives, which deepen our understanding of mobile social media use behaviors at the individual level. Second, it is the first study that examines unobserved heterogeneity and international microsegmentation in the mobile social media domain. I revealed that global mobile social media users are heterogeneous. Moreover, global users from different countries may have similar behavioral patterns, cultural value orientations, and demographic characteristics. Thus, mobile social media firms should incorporate international segmentation into marketing strategies and develop specific market offerings according to the specific behavioral patterns, cultural values, and demographic characteristics of each segment.

The third chapter contributes to the social media competitive intelligence literature. First,

I refined the existing social media competitive intelligence frameworks by incorporating the prediction phase into the existing frameworks. Thus, the scopes of the current social media competitive intelligence frameworks have been extended from intelligence extraction to making use of intelligence for customer behavior prediction. Second, I illustrated how to implement the proposed social media competitive intelligence framework through a case study. The results provide insights into the evolutionary trends of sentiments and topics in the catering industry before and during the pandemic that guide firms to make the right decisions that enhance customer engagement in social media.

3. Methodology used

To understand how firms and customers apply mobile social media to create and exchange value, in the first chapter, I developed a framework of value creation in mobile social media after reviewing the existing studies. The systematic literature review was conducted following three steps: keyword search, study selection, and data extraction. In the step of keyword search, studies were searched in two scientific literature databases: Web of Science and Scopus, which are internationally accessible and contain high-quality literature. In particular, the following keywords were searched in the title, abstract, keywords, and full text of the articles: “mobile social media,” “mobile social network,” “mobile social networking sites,” “mobile instant messaging.” Later, I conducted a manual cross-referencing to identify further studies. In the step of study selection, four inclusion and exclusion criteria were applied to select the studies. First, the area of the publications should be business and management. Second, the publications should be in English. Third, the publications should be journal articles. Fourth, the focus of the

investigation should be value creation or value for firms and customers in mobile social media. In the step of data extraction, a total of 53 articles were identified. A thematic analysis was used to propose a novel and integrative conceptual framework and illustrate the value transition paths between firms and customers. Specifically, I adopted a narrative synthesis perspective to review the literature.

To achieve the objectives of the second chapter, the data was collected via an online survey method in two countries: China and the United States. The two countries were selected for the following reasons. First, both countries have a large number of social media users around the world (64.6% in China and 72.3% in the United States) (We are social & Hootsuite, 2021). Second, the cultural value orientations of these two countries are profoundly different (G. Hofstede, 2001). Third, some of the characteristics, such as their diverse and multicultural populations, indicate a high probability of the existence of unobserved customer heterogeneity.

Before collecting the data, a quota sampling was applied to select survey participants in both countries. Moreover, the proportions of age and sex intervals were controlled to resemble the countries' populations. In particular, the participants from both countries have accessed social media via mobile devices during the last six months. For the data collection, different platforms were used in the two countries. In China, I contracted an online panel company, Wenjuanxing, to distribute the survey among Chinese respondents, and 420 valid responses were received. In the United States, the survey was distributed to American respondents on the Amazon Mturk platform, and 424 valid responses were collected. Regarding data analysis, the study firstly applied partial least squares path modeling (PLS-SEM) to estimate the research model. Further, the study adopted Response Based Unit Segmentation in PLS path modeling

(REBUS-PLS) to detect unobserved heterogeneity and segment users with similar behavioral patterns.

For the third chapter, a social media competitive intelligence framework was proposed to illustrate how to extract intelligence from social media data and then use the gained intelligence to predict customer engagement and make decisions. Then, I describe the implement of the proposed framework through a case study. I collected tweets generated by the leading American catering brands using Application Programming Interface (API). The catering industry was selected as the context because it was one of the most influenced industries during the COVID-19 pandemic (Brewer & Sebby, 2021; Sharma et al., 2020; Yang et al., 2020). Due to the prevention measures during the epidemic, the opening hours of many restaurants are greatly restricted, and people in many countries cannot dine in the restaurant. American brands were chosen because the United States was one of the most impacted countries by the COVID-19 pandemic regarding infection and death rate (Our World in Data, 2021). The study was conducted through two phases. In the first phase, I explored changes in the sentiments and topics of tweets generated by catering brands before and during the COVID-19 pandemic. A cloud-based machine learning service, Amazon Comprehend, was used to obtain the sentiment labels for the tweets, and we employed the LDA algorithm to explore the topics among the textual data. In the second phase, the structured textual data along with other originally structured data were used to predict customer engagement in social media. Specifically, six state-of-art machine learning algorithms were tried to specify the classification model, which are Support vector machine (SVM) with radial basis kernel, CART tree, C5.0 tree, Random forest, Bagged CART, and Gradient Boosting.

4. Final conclusions

The thesis reveals that social media and mobile social media are effective value creation tools in the modern marketing era. With mobile social media, firms create value for customers by providing an improved communication channel, customized services, and promotions. Through this approach, firms also enhance their brand images and customer relationship management. At the same time, firms can capture value from customers in return, such as customer knowledge, market insights, customer satisfaction, customer loyalty, and customer equity. Moreover, customers can co-create value by participating in Electronic Word-Of-Mouth, being opinion leaders, generating the content, and making contributions to product and brand co-design and innovation.

From the perspective of value creation at the customer level, individuals' mobile social media use behavior is the premise of value creation. Attitude towards mobile social media is a key factor that drives individuals' use behavior. Moreover, motivation theory has more explanatory power on attitude and use behavior than social influence theory. Furthermore, global mobile social media users are heterogeneous. Through *post hoc* segmentation based on users' behavioral patterns, global users can be segmented into three groups, which are significantly different in terms of behavioral patterns, cultural values, and demographic characteristics. Thus, incorporating international segmentation into marketing strategies is essential for mobile social media firms that operate in foreign markets. There is a need to design and develop mobile social media applications based on the specific needs, use patterns, and characteristics of global users in specific international segments.

From the perspective of value creation at the firm level, firms create greater value by leveraging competitive intelligence gained from social media data. On the one hand, the knowledge gained from social media data generated by corporate users, such as sentiments and topics, enables firms to identify current industrial changes in the environment and competitors' marketing strategies. On the other hand, the gained competitive intelligence also sheds light on what is going to happen in the future. Such information is extremely useful during extreme events or crises. It guides firms to adapt their marketing strategies to the new environment. The results of the case study show that environmental uncertainty affects firms' social media strategies. Moreover, the importance of the predictors toward customer engagement, such as sentiments and topics, differs in normal and pandemic situations.

CONCLUSIONES FINALES

La tesis revela que las redes sociales y las redes sociales móviles son herramientas efectivas de creación de valor en la era moderna del marketing. Con las redes sociales móviles, las empresas crean valor para los clientes mediante proporcionar un canal de comunicación mejorado, servicios personalizados y promociones. De tal manera, las empresas también mejoran la imagen de su marca y la gestión de las relaciones con los clientes. Al mismo tiempo, las empresas pueden obtener los valores de los clientes a cambio, como el conocimiento del cliente, la inteligencia del mercado, la satisfacción del cliente, la lealtad del cliente y la equidad del cliente. Además, los clientes pueden co-crear valor mediante participar en el *electronic Word-Of-Mouth*, ser líderes de opinión, generar contenido y hacer contribuciones al co-diseño e innovación de productos y marcas.

Desde la perspectiva de la creación de valor a nivel del cliente, el comportamiento de uso de las redes sociales móviles es la premisa de la creación de valor. La actitud hacia las redes sociales móviles es un factor clave que impulsa el comportamiento de uso. Además, la teoría de la motivación tiene más poder explicativo sobre la actitud y el comportamiento de uso que la teoría de la influencia social. Además, los usuarios de redes sociales móviles al nivel mundial son heterogéneos. A través de la segmentación *post hoc* basada en los patrones de comportamiento, los usuarios globales pueden segmentarse en tres grupos, que son significativamente diferentes en términos de patrones de comportamiento, valores culturales y características demográficas. Por lo tanto, incorporar la segmentación internacional en la estrategia de marketing es esencial para las empresas de redes sociales móviles que operan en mercados extranjeros. Hay que diseñar y desarrollar aplicaciones de redes sociales móviles

basadas en las necesidades específicas, los patrones de uso y las características de los usuarios globales en cada uno de los segmentos internacionales.

Desde la perspectiva de la creación de valor a nivel de empresa, las empresas crean mayor valor aprovechando la inteligencia competitiva obtenida de los datos de las redes sociales. Por un lado, los conocimientos obtenidos de los datos de redes sociales generados por los usuarios corporativos, tales como sentimientos y temas, permite a las empresas identificar los cambios industriales actuales en el medio ambiente y las estrategias de marketing de los competidores. Por otro lado, la inteligencia competitiva obtenida también revela qué va a ocurrir en el futuro. Dicha información es extremadamente útil durante eventos extremos o crisis, que orienta a las empresas para adaptar sus estrategias de marketing al nuevo entorno. Los resultados del estudio de caso muestran que la incertidumbre ambiental afecta las estrategias de las empresas en las redes sociales. Además, la importancia de los predictores para el compromiso del cliente, tales como los sentimientos y los temas, varían en las situaciones normales y pandémicas.

APPENDIX

Two of the three chapters have been published in the journals indexed in the Journal Citation Reports (JCR). The journals' information and the Ph.D. student's contributions are shown below.

Article 1

Title: Value creation in mobile social media: a systematic review and agenda for future research

Journal: Baltic Journal of Management

Authors: Xingting Ju, Oscar Martín Martín, and Raquel Chocarro Eguaras

Introduction to the journal: Baltic Journal of Management was established in 2006. It publishes peer-reviewed research on major disciplines in management, and four issues of empirical and theoretical studies are published per year. Initially, the journal focuses on topics related to management and organizational topics of importance to those in and beyond the Baltic sea region. Now the journal publishes international perspectives on contemporary matters and emerging fields in management, such as international business and management, marketing and consumer studies, innovation and digital technology, and strategic and operations management.

Information of the journal in the Journal Citation Reports (JCR) (2020):

Impact factor: 2.897

JCR Category: Management

Category Rank: 153/226

Category Quartile: Q3

Ph.D. student's contributions: The author has contributed significantly to all stages of the research, including the statement of the objectives, literature review, research design, synthesis of the results, writing of the original manuscript, and writing of the revised manuscript.

Article 2

Title: Determinants of mobile social media use, customer heterogeneity, and international microsegmentation

Journal: International Journal of Consumer Studies

Authors: Xingting Ju, Oscar Martín Martín, and Raquel Chocarro Eguaras

Introduction to the journal: International Journal of Consumer Studies was established in 1970 and was named Journal of Consumer Studies & Home Economics before 2001. It is a peer-reviewed academic journal that publishes six issues of empirical and theoretical studies per year. The journal publishes articles of interest to an international audience, and its scope focuses on consumers, such as consumer behavior, consumer education, consumer psychology, marketing research, and information technology.

Information of the journal in the Journal Citation Reports (JCR) (2020):

Impact factor: 3.864

JCR Category: Business

Category Rank: 82/153

Category Quartile: Q3

Ph.D. student's contributions: The author has contributed significantly to all stages of the research, including the statement of the objectives, literature review, formulation of the hypotheses, research design, programming language coding, data analysis, writing of the original manuscript, and writing of the revised manuscript.

Article 3

This chapter is yet to be published. The Information of the targeted journal is shown below.

Title: A social media competitive intelligence framework for customer engagement prediction and decision support

Journal: International Journal of Research in Marketing

Authors: Xingting Ju, Raquel Chocarro Eguaras, and Oscar Martín Martín

Introduction to the journal: The International Journal of Research in Marketing was born in 1984. *IJRM* is an international, double-blind peer-reviewed journal and publishes four issues per year. The aim of *IJRM* is to advance marketing knowledge and techniques, and its audience includes marketing scholars, practitioners, and policymakers. The journal embraces innovative research with the potential to spur future research and influence practice, especially encourages research that is novel, visionary, or pathbreaking.

Information of the journal in the Journal Citation Reports (JCR) (2020):

Impact factor: 4.513

JCR Category: Business

Category Rank: 70/153

Category Quartile: Q2

Ph.D. student's contributions: The author has contributed significantly to all stages of the research, including the statement of the objectives, literature review, research design, programming language coding, data analysis, and writing of the original manuscript.

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Ju, X., Chocarro, R. and Martín Martín, O. (2021), "Value creation in mobile social media: a systematic review and agenda for future research", *Baltic Journal of Management*, Vol. 16 No. 5, pp. 745-764.
<https://doi.org/10.1108/BJM-04-2021-0157>

Copy of article 2

Determinants of mobile social media use, customer heterogeneity, and international microsegmentation

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Abstract

How to effectively examine the heterogeneous nature of consumer preferences across borders and cultures is a challenge for firms that use mobile social media. This study identifies the determinants of individuals' mobile social media use behavior and profiles the resulting international microsegments. We propose a model that integrates different theoretical perspectives and sets of factors to explain mobile social media use behavior and test it on a sample of users in China and the United States via online surveys. We estimate a global model (GM) based on all respondents and three local models created by post hoc international microsegmentation. The three local models reveal the existence of three unobserved user segments: "usage goal experts," "determined pragmatists," and "pressured hedonists." Perceived usefulness is the most influential factor in the GM, while users in the three segments significantly differ in their behavioral patterns, cultural value orientations, and demographic characteristics. This study is the first to examine unobserved heterogeneity and international microsegmentation in the mobile social media domain. It provides insights into the factors explaining use behavior and international microsegmentation for scholars and marketers operating in the global marketplace.

KEYWORDS

cross-cultural, international segmentation, microsegmentation, mobile social media, unobserved heterogeneity

1 | INTRODUCTION

Mobile social media are social applications that can be accessed via smartphones for the purpose of communication, interaction, and the generation and exchange of content for many users. They include social networking sites (e.g., Facebook) and instant messaging platforms (e.g., WhatsApp). Mobile applications are portable, personalizable, interactive, convenient, and effective (Huang et al., 2019). Therefore, mobile social media are used globally and are important for firms and marketers as effective tools to create

and capture customer value (Ju et al., 2021). Social media are being increasingly used on mobile devices rather than other devices (Mehra et al., 2020), and several of their characteristics, such as their effective real-time communication (Hwang & Nam, 2017; Yang et al., 2021) and personalizable services (Cloarec, 2020; Pagani & Malacarne, 2017), distinguish mobile social media from traditional social media (Kaplan, 2012).

Marketing 4.0 has a significant impact on customers' satisfaction and purchase intention and implies a more "inclusive, horizontal and social approach to marketing" (Dash et al., 2021, p. 609) in which

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social media can play a relevant role. The ubiquity of social media influences individuals' behavior (Lamberton & Stephen, 2016) and provides new opportunities for researchers and firms that operate in global markets (Rosado-Serrano & Paul, 2017). Particularly, mobile social media use behavior and international segmentation are important research topics that deserve more attention from marketing scholars, as argued below.

Research on social media and mobile social media use behavior has flourished in recent years and falls into two streams. The first stream has primarily focused on the antecedents of continuous usage intention (e.g., Gao & Bai, 2014; Gong et al., 2018; Han et al., 2015; Hoehle et al., 2015; Hong et al., 2017; Leong et al., 2018; Lien et al., 2017; Shao & Pan, 2019; Tan et al., 2018; Wang, 2020; Yang & Lin, 2019; Zhang et al., 2017; Zhao et al., 2016), adoption intention (e.g., Lin & Lu, 2015; Wang, 2020), active use (e.g., Bailey et al., 2018; Pagani & Malacarne, 2017; Shao & Pan, 2019), and actual use (e.g., Assimakopoulos et al., 2017; Ha et al., 2015; Hyun et al., 2021). Studies belonging to this stream have mainly applied different theoretical lenses and, therefore, have used different sets of factors as determinants of mobile social media use behavior.

The second research stream has focused on cross-cultural analysis and has applied Hofstede's cultural value dimensions (Hofstede, 2001) to examine social media and mobile social media use (Abbas & Mesch, 2015; Alsaleh et al., 2019; Amaro & Duarte, 2017; Hoehle et al., 2015; Ifinedo, 2016; Jackson & Wang, 2013; Makri & Schlegelmilch, 2017; Sheldon et al., 2017). Since firms cannot serve the world's heterogeneous population using standardized marketing strategies, researchers and marketers have shown an increasing interest in assessing the heterogeneous nature of customers, and in segmenting them (Steenkamp & Hofstede, 2002).

However, little research exists on heterogeneity and the international segmentation of mobile social media users, and two limitations affecting prior mobile social media research and international microsegmentation are particularly relevant to the current study. First, from the few studies on the actual use of mobile social media, researchers have mainly shed light on the effect of hedonic and integrative gratifications on users' attitudes toward the platforms, as well as their actual use behavior (Ha et al., 2015). However, users' attitudes may be affected not only by perceived hedonic (intrinsic motivation) and integrative gratifications but also by factors such as extrinsic motivations and the perceived influence of their social environment. Thus, identifying the determinants of users' attitudes and actual use behavior from multiple theoretical perspectives is expected to provide a more comprehensive explanation of mobile social media use behavior and mitigate the problem of utilizing more simplistic frameworks that do not integrate some of the relevant factors that drive their usage.

Second, when researchers have conducted cross-cultural analyses to explore users' behavioral differences, the country has been the most frequently used criterion for classifying users (Hoehle et al., 2015). Users in a country are typically assumed to

display similar behavioral patterns and cultural values (Hoehle et al., 2015). However, when there are minimal differences in users' behavioral patterns across countries, the country becomes less important as a segmentation variable (Marreiros et al., 2020). A priori segmentation, as a segmentation approach that groups consumers based on predefined segmentation variables such as demographics (e.g., nationality) rather than on market research, may hide differences in consumer behavior when heterogeneous behavioral patterns exist (Wedel & Kamakura, 2002). Therefore, post hoc segmentation, as a method in which respondents are clustered according to consumer data and the similarity of multivariate individual profiles (Kalafatis & Cheston, 1997), is a more suitable approach.

Against this background, this study's objectives are to bridge these gaps by integrating from several theoretical perspectives the factors that drive actual mobile social media use behavior and by uncovering the different behavioral patterns, cultural value orientations, and demographic characteristics across international microsegments. More specifically, this study seeks to answer the following research questions: (a) How do intrinsic and extrinsic motivations, technology acceptance, and social influence explain the attitude toward and mobile social media use? (b) How can post hoc international microsegmentation of behavioral patterns be effectively applied to identify users' heterogeneity in mobile social media use?

To answer these questions, we propose a hybrid model that integrates the technology acceptance model (TAM) (Davis, 1986; Davis et al., 1989), motivation theory (Deci & Ryan, 1987), and social influence theory (Kelman, 1958) as the main foundations for examining individuals' attitude and actual use behavior. We apply partial least squares path modeling (PLS-SEM) (Hair Jr et al., 2016) to estimate the model using a sample of mobile social media users collected in China and the United States via online questionnaires. Then, we adopt Response Based Unit Segmentation in PLS path modeling (REBUS-PLS) (Vinzi et al., 2008) to detect unobserved heterogeneity and segment users with similar behavioral patterns. Finally, we explain the behavioral differences across segments through the lens of cross-cultural variation theory (Hofstede et al., 2010) and demographic variables.

Our study offers two contributions to the literature on mobile social media and international microsegmentation. First, it identifies and integrates, from multiple theoretical perspectives, different sets of factors that ultimately drive users' actual use behavior, which can help scholars and firms to understand users' preferences and behaviors more comprehensively. Second, our study also contributes to the under-researched topics of unobserved heterogeneity and international microsegmentation in mobile social media by effectively detecting unobserved heterogeneity and segmenting users from different countries who share behavioral patterns. Knowledge regarding different user groups, including the most influential factors, demographic characteristics, and cultural values at the individual level, can help firms more effectively tailor their market offerings toward each segment.

2 | MOBILE SOCIAL MEDIA USE AND INTERNATIONAL MARKET SEGMENTATION

2.1 | Mobile social media use

To review the literature on mobile social media use, we searched for publications in ScienceDirect, Scopus, and Web of Science because of the internationally accessible and high-quality literature contained therein (Ju et al., 2021; Misirlis & Vlachopoulou, 2018; Salo, 2017). We limited our selection to peer-reviewed articles published in journals listed in the Journal Citation Reports (JCR). These publications represent the most advanced level of research in their corresponding fields (Mustak et al., 2013). We used the following keywords in the title, abstract, keywords, and full text of the articles (Paul & Criado, 2020): “mobile social media,” “mobile social networking sites,” “mobile SNS,” “mobile social media applications,” “mobile social apps,” “mobile instant messaging,” and “mobile location-based social networks.” We found 17 suitable studies; Table 1 summarizes their objectives, theories, methodologies, and contributions.

Studies focusing on mobile social media use behavior can be traced back to 2014 (see Table 1, column one), and have investigated the antecedents that drive individuals' use behavior (see Table 1, column two). Researchers have primarily studied continuous usage intention (Gao & Bai, 2014; Gong et al., 2018; Han et al., 2015; Hoehle et al., 2015; Hong et al., 2017; Leong et al., 2018; Lien et al., 2017; Shao & Pan, 2019; Tan et al., 2018; Wang, 2020; Yang & Lin, 2019; Zhang et al., 2017; Zhao et al., 2016) but have paid less attention to initial usage intention (Lin & Lu, 2015; Wang, 2020), actual use behavior (Ha et al., 2015), and active and passive behavior (Pagani & Malacarne, 2017).

Various theories have been adopted to explain mobile social media use behavior. The TAM (Davis, 1986; Davis et al., 1989) is the most widely used theory, and studies on mobile social media have highlighted the significant role of the perceived usefulness and perceived ease of use in using technology (Leong et al., 2018; Oghuma et al., 2016; Tan et al., 2018; Zhao et al., 2016). In addition, gratification theory (Katz et al., 1973) has also been widely used. Researchers have found several gratifications perceived from mobile social media use that positively affect individuals' use behavior, as follows. Social gratification satisfies users' social connection needs (Han et al., 2015), hedonic gratification satisfies users' entertainment and enjoyment needs (Ha et al., 2015; Hsiao et al., 2016; Yang & Lin, 2019), utilitarian gratification satisfies users' needs to contact others and obtain information, and integrative gratification satisfies users' needs to form a sense of belonging to a group and enhance personal values (Ha et al., 2015). In addition, researchers have highlighted motivation theory (Deci & Ryan, 1987) to explain users' behavior. Specifically, perceived usefulness is classified as an extrinsic motivation (Lin & Lu, 2011; Wamba et al., 2017), whereas hedonic gratification is an intrinsic motivation (Zhang et al., 2017). Finally, the perceived social influence of other users also plays an important role in driving users' behavior (Gao & Bai, 2014; Lin & Lu, 2015; Zhang et al., 2017; Zhao et al., 2016).

All the studies were quantitative and conducted data collection via online surveys. The most frequent country for data collection was Mainland China (see Table 1, column four); however, for our purposes, we only found one cross-cultural study (Hoehle et al., 2015) that explained use. All studies applied structural equation modeling (SEM) to analyze the hypothesized relationships. By exploring the antecedents of mobile social media use, these studies deepen our understanding of individuals' behavior and provide useful insights to mobile social media developers and marketing practitioners (see Table 1, column five).

Very little research has considered the role of attitudes toward mobile social media, or the corresponding antecedents that form such attitudes (e.g., Ha et al., 2015). Attitude is an important component in the behavioral process of using information systems because it constitutes a key affective response that connects cognitive and behavioral responses (Davis, 1986; Davis et al., 1989). The current study considers the role of attitude to connect actual use with several cognitive components.

2.2 | International market segmentation

Globalization of the business world has turned international market segmentation into an essential concept in both marketing theory and practice (Wedel & Kamakura, 2002). Market segmentation is the process of dividing a heterogeneous market into smaller and relatively homogeneous segments (Kale & Sudharshan, 1987). It can help identify groups of consumers that are separated by national or cultural boundaries but have similar needs and wants (Grunert, 2019). Segmentation helps companies address consumers' specific needs and target potential customers at the international segment level (Steenkamp & Hofstede, 2002). However, how to effectively deal with both the structure of heterogeneity in customers' needs and wants and segment consumers across borders are among the main challenges for scholars and international marketers (Steenkamp & Hofstede, 2002). International segmentation is a challenging issue because it involves obtaining comparative information pertaining to not only countries, industries, products, and consumers in a given market, but also to the cultures of the markets (Papadopoulos & Martín Martín, 2011).

The evolution of the Internet toward the more interactive Web 2.0, the new online platforms for marketing research, and the growth of social media have resulted in both an increase in the availability of data at the consumer level and opportunities for new studies on international (micro)segmentation. Most international segmentation studies have ignored individual heterogeneity by using the country as the unit of analysis (for exceptions, see Cleveland et al., 2011) and they have not focused on segmenting mobile social media users. Taking the country as the unit of analysis, Gaston-Breton and Martín Martín (2011) proposed a two-stage market selection and segmentation model that integrated market attractiveness and consumer values to help institutions and market-seeking multinational enterprises segment European macro-regions and groups of consumers.

TABLE 1 Main studies on factors explaining mobile social media use

Author	Objective	Theory	Methodology	Contribution
Gao and Bai (2014)	To identify the factors affecting mobile SNS users' continuance intention.	IS success model, Network externalities, Flow	Structural equation modeling, 228 responses were collected in Mainland China via survey.	The study enriches extant research on postadoption usage of mobile SNS by integrating network externalities, flow theory, and IS success model.
Ha et al. (2015)	To examine the factors that drive mobile social media users' actual use behavior.	Perceived value, Prospect theory & mental accounting theory	Structural equation modeling, 330 responses of KakaoTalk and 311 of Facebook users were collected via survey in South Korea.	This study deepens the understanding of users' postadoption of mobile SNSs by examining the effect of media effects on actual user behavior.
Han et al. (2015)	To investigate the antecedents of continuous usage intention of SNSs and to compare the differences between mobile and nonmobile users.	Uses and Gratifications Theory	Structural equation modeling, Responses from 798 Twitter users were collected via a cross-sectional survey in South Korea.	This study examines the impact of immediacy and intimacy on social presence and illustrates the different impact of mobile and desktop on social presence.
Hoehle et al. (2015)	Conducting a four-country study to examine factors that drive users' continued usage intention and to explore the differences under the impact of culture.	Espoused cultural values	Structural equation modeling, 1,844 responses were collected via survey from the United States, Germany, Mainland China, and India.	This study shows that espoused national cultural values do not play an important role in moderating the impact of mobile social media application usability on continued intention to use.
Lin and Lu (2015)	To predict individuals' acceptance of mobile social network.	Value theory, social influence	Structural equation modeling, 318 responses were collected via survey in Taiwan.	This study enriches our understanding of factors that explain users' intention to use the mobile SNSs.
Hsiao et al. (2016)	To explore the influential factors in the continuance intention of social App use.	Utilitarian motivation, Hedonic motivation, social influence	Structural equation modeling 378 responses were collected via survey in Taiwan.	The study explains users' initial adoption of the continued use of social Apps from the perspective of customer values.
Oghuma et al. (2016)	To examine the drivers of MIM users' continuance intention.	Expectation Confirmation Theory, post-Expectance Model of IS Continuance	Structural equation modeling, 350 KakaoTalk users were collected via survey.	The study extends the Expectation Confirmation Theory from IS use in general to MIM use by verifying the impact of perceived usability, perceived security, perceived service quality, and confirmation on continuous usage intention.
Zhao et al. (2016)	To examine antecedents in enhancing customer engagement and long-term loyalty in mobile social media LINE.	Technology Acceptance Model, Theory of psychological ownership	Structural equation modeling 791 responses of Line users were collected via survey in Taiwan.	The study contributes to social media literature by examining the effects of critical factors based on TAM and psychological ownership on users' loyalty to social media.
Lien et al. (2017)	To examine the impact of service quality on WeChat users' usage intention.	Expectancy-Disconfirmation theory	Structural equation modeling, 639 respondents were collected via survey in Mainland China.	The study verified the impact of interaction quality, environment quality, and outcome quality on WeChat users' satisfaction, and confirmed the mediating role of stickiness between satisfaction and usage intentions.

(Continues)

TABLE 1 (Continued)

Author	Objective	Theory	Methodology	Contribution
Pagani and Malacarne (2017)	To explore how social media and mobile influence users' online dynamic behavior.	Customer engagement, Experiential engagement, Active and passive use with location-based services	Structural equation modeling 379 responses were collected via survey in EU and the United States.	This study provides insights into increasing experiential engagement and mitigating the negative influence of privacy concerns on the active use of location based SNSs.
Zhang et al. (2017)	To examine the effects of network externalities on users' perceived values and continuance intention.	Network externalities, social interaction ties, Perceived values	Structural equation modeling, 240 responses of WeChat users were collected via survey in Mainland China.	This study provides insights into users' postadoption behavior of SNS by testing the mediating role of social interaction ties in the effect of network externalities on different perceived values.
Gong et al. (2018)	To explore the reasons why experienced mobile social apps users are likely to continue using the app.	Experiential learning theory	Structural equation modeling, 295 responses of WeChat users were collected via survey in Mainland China.	This study enriches our understanding of users' postadoption behavior of mobile social media and the role of levels of experience in increasing their continuous usage intention.
Leong et al. (2018)	To explore the determinants of students' usage intention of mobile SNSs for their pedagogical purposes.	Technology Acceptance Model	Structural equation modeling, 600 students from public universities of Malaysia filled out the survey.	The study extended TAM by confirming the moderating effect of experience on the intention to mobile social media adoption for pedagogical purposes.
Tan et al. (2018)	To understand consumers' adoption intention of mobile social media advertising.	Technology Acceptance Model, personal factors, Interactivity Theory	Structural equation modeling, 459 data were collected in Malaysia via survey.	The study extended TAM by with consumers' personal factors and interactivity.
Shao and Pan (2019)	To examine the factors that drive users' behaviors in the WeChat Moments.	Social capital theory, Technology affordance theory	Structural equation modeling, 287 data were collected from WeChat users in Mainland China via survey.	The study enriches our understanding of antecedents of user participation in mobile social media.
Yang and Lin (2019)	To examine the antecedents that drive elderly users' mobile social service adoption.	Uses and gratification theory, Media richness theory	Structural equation modeling, 226 valid data were collected via survey in Taiwan.	The study advances our understanding of elder users' mobile social media service adoption behavior by proposing a framework combining uses and gratification theory and media richness theory.
Wang (2020)	To understand antecedents that drive mobile short-form video apps adoption intention.	Human-Computer Interaction theory	ANCOVA, 81 responses were collected via survey in the United States.	The study addresses the effects of short-form videos characteristics on users' psychological responses and adoption intention.

Budeva and Mullen (2014) focused on the economic and cultural factors that affected international country segments, and their stability over time, in 30 countries. Cleveland et al. (2011) studied urban consumers from eight countries and found that ethnic identity and demographics impacted consumer behavior. Wamba et al. (2017) assessed unobserved heterogeneity in the information system field by segmenting user social media acceptance within the workspace in five countries.

Although globalization may increase the similarity in needs and wants across national boundaries, countries and mobile social media users remain largely heterogeneous in their preferences and behaviors, and researchers have not paid attention to the heterogeneous nature and international microsegmentation of mobile social media users.

3 | THEORETICAL FRAMEWORK AND HYPOTHESES

This section proposes a hybrid model of actual mobile social media use based on the TAM, motivation theory, and social influence theory (see Figure 1), and explains the impact of heterogeneity in mobile social media use. The TAM was built based on the theory of reasoned action (TRA) (Ajzen & Fishbein, 1980) to explain information system acceptance. The TAM posits that users' attitude toward use is a predictor of behavioral intention, which, in turn has a direct effect on actual use. Users' attitudes are jointly determined by perceived usefulness and perceived ease of use (Davis, 1986; Davis

et al., 1989). Motivation theory (Deci & Ryan, 1987) connects the cognitive responses arising from perceived usefulness, ease of use, and enjoyment with the affective response of attitude toward use. Social influence theory was proposed by Deutsch and Gerard (1955) and Kelman (1958), and indicates that referent others influence an individual's attitudes, beliefs, and subsequent actions or behaviors. Building on social influence theory, we complete the model with subjective norms, referent network size, and attachment motivation as other sets of determinants of attitude toward use.

3.1 | Motivation theory and TAM factors

3.1.1 | Perceived enjoyment

We define *perceived enjoyment* as the extent to which the activity of using mobile social media is perceived to be enjoyable. It is an intrinsic and hedonic motivation driven by internal rewards such as enjoyment (Davis et al., 1992; Lee et al., 2005; Venkatesh, 2000; Venkatesh & Bala, 2008). Users may adopt mobile social media not only for communication or interaction (Ju et al., 2021), but also for the enjoyment that is obtained from the usage process (Zhou & Lu, 2011). Thus, perceived enjoyment can be seen as a crucial factor that affects users' adoption behavior (Ha et al., 2015; Hsiao et al., 2016; Omoush et al., 2012; Pagani & Malacarne, 2017; Zhou & Lu, 2011).

People may form beliefs about an object by associating it with specific attributes, and may form attitudes from beliefs (Fishbein &

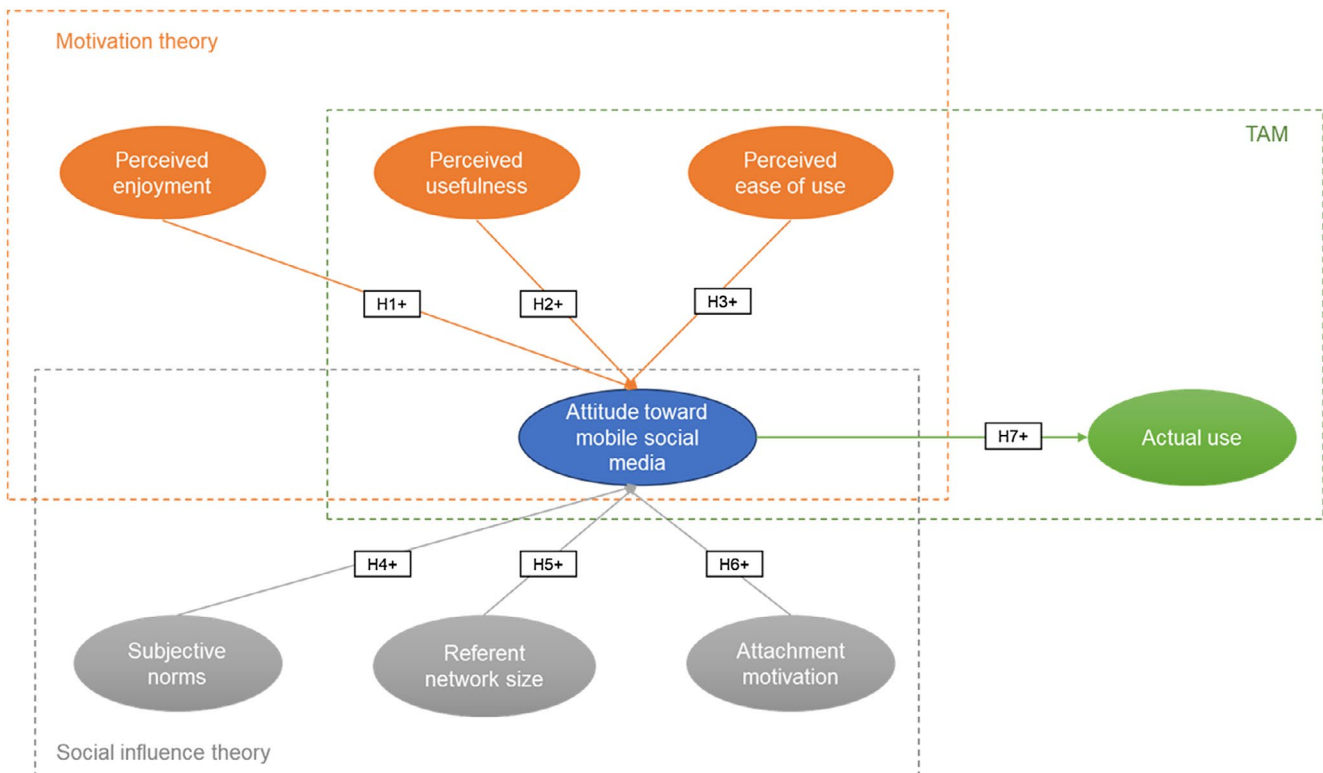


FIGURE 1 Research model

Ajzen, 1975). Social psychologists have proposed that attitude formation can occur through direct experience and emotional reactions (Bem, 1970). Thus, when users experience enjoyment from the use of a given technology, they may form a positive attitude toward it. Consistent with this logic, in the social media sphere, Chen (2014) found that the more pleasure users obtained from using Facebook, the more positive their attitudes toward the social network were. Similarly, Bailey et al. (2018) explored social media use behavior among young users and showed that perceived enjoyment was positively related to users' attitudes toward social media. Thus, we suggest that the perceived enjoyment of mobile social media also leads users to form a favorable attitude toward it. Therefore, we propose the following hypothesis:

H1. Perceived enjoyment is positively related to attitude toward mobile social media.

3.1.2 | Perceived usefulness

Based on Davis et al. (1992), we define *perceived usefulness* as user expectations that their use of mobile social media will improve the effectiveness of achieving their goals. Motivation can also be extrinsic (Deci & Ryan, 1987). Extrinsic motivation refers to user behavior that is driven by external rewards, such as improved job performance, salary, or promotion (Davis et al., 1992; Venkatesh & Bala, 2008). Perceived usefulness is an extrinsic motivator (Davis et al., 1992; Kwon et al., 2021; Venkatesh & Bala, 2008; Wamba et al., 2017; Zhou & Lu, 2011) because it represents a user's utilitarian need for social media platforms (Hong et al., 2017; Hsiao et al., 2016).

Previous social media studies have shown that users may form a positive feeling about platforms when their usage experience matches their expectations (Bailey et al., 2018; Gao et al., 2013; Im & Ha, 2013; Lee et al., 2005; Lin & Kim, 2016). Gao et al. (2013) found that consumers in the United States, mainland China, and Europe formed a positive attitude toward mobile marketing when they increased their perceived utility in participating in marketing activities using mobile technology. Notably, perceived usefulness is the most influential factor affecting American consumers' attitudes toward mobile marketing (Gao et al., 2013). Therefore, we propose the following hypothesis:

H2. Perceived usefulness is positively related to attitude toward mobile social media.

3.1.3 | Perceived ease of use

We define *perceived ease of use* as the extent to which a person believes that using mobile social media will be free from effort. A given technology's ease of use may be inferred from

the effort put into the process of using the technology to accomplish a task (Davis et al., 1992). Less effort would imply a higher value for the user and, therefore, a positive attitude toward the technology.

Previous social media studies have indicated that users may have a positive attitude toward technology when they have had a good experience and have made less effort previously to complete personal goals (Bailey et al., 2018; Gao et al., 2013; Im & Ha, 2013; Lee et al., 2005). Since social media constitutes important advertising channels (Sreejesh et al., 2020), Lin and Kim (2016) examined undergraduate students' acceptance of sponsored advertising on Facebook. They showed that the easier use of Facebook advertising resulted in a positive attitude toward Facebook advertising. Thus, we suggest that users will form a positive attitude toward mobile social media when less effort is required to use their functions. Therefore, we propose the following hypothesis:

H3. Perceived ease of use is positively related to attitude toward mobile social media.

3.2 | Social influence factors

3.2.1 | Subjective norms

Subjective norms are one of the root constructs of social influence (Venkatesh et al., 2003). This influence means that a user's decision to use an information system is influenced by people who are important to them, including family, friends, and colleagues (Venkatesh & Bala, 2008). In the information system context, subjective norms can be considered as the psychological pressure perceived by peers regarding technology adoption (Davis, 1986), and they play an essential role in influencing users' attitudes and decision-making processes. Generally, people may choose to perform a behavior if they believe that one or more essential referents think they should (Venkatesh & Davis, 2000). Subjective norms may influence behavioral intentions via attitude (Davis et al., 1989).

We suggest that a previous positive influence on the use of mobile social media from relevant referents may lead to a positive attitude toward this technology. Prior studies have shown that subjective norms influence users' attitudes toward a given technology. Specifically, Im and Ha (2013) examined American consumers' adoption decisions regarding mobile coupons, and found a positive relationship between subjective norms and attitude. That is, individuals were more likely to form a positive attitude toward the given technology when their peers believed that the technology should be used (Im & Ha, 2013). In the context of social media, Chen (2014) found that subjective norms positively affected user attitudes toward Facebook. We posit that users may form a favorable attitude toward mobile social media under social pressure. Therefore, we propose the following hypothesis:

H4. Subjective norms are positively related to attitude toward mobile social media.

3.2.2 | Referent network size

The *referent network size* refers to the number of participants in a social network. This aspect represents the perceived value of direct network externalities (Lin & Bhattacharjee, 2008). The value of technology increases to a person when others use it (Shepherd & Lane, 2019), and because of this “herd effect” (Hong et al., 2017), users’ usage decisions regarding interactive technologies are often influenced by the number of friends and colleagues who use them in their social circle. The number of people with whom users can communicate increases with the number of people who use IT (Lin & Bhattacharjee, 2008). In contrast, when the referent network size is small, users may have less interest in a technology and stop using it (Zhou & Lu, 2011).

Although empirical studies have verified the impact of the referent network size on network benefits (Lin & Bhattacharjee, 2008) and perceptual outcomes (Hong et al., 2017), no study has yet examined its impact on users’ attitudes toward mobile social media. Under the influence of the “herd effect,” people are more likely to believe in the evaluation of and feelings toward the mobile social media used by their reference groups, and imitate their adoption decisions (Hong et al., 2017). Thus, users’ attitudes toward mobile social media may be more positive as the number of users increases. Therefore, we propose the following hypothesis:

H5. The referent network size is positively related to attitude toward mobile social media.

3.2.3 | Attachment motivation

Attachment motivation is the degree to which individuals believe that they can improve their social interactions and interpersonal relationships via mobile social media (Ma & Chan, 2014). In the current study, attachment reflects the emotional bond connecting an individual to mobile social media platforms. Social media serve not only to communicate, create, and share messages with others (Yannopoulou et al., 2019), but also shape people's thoughts and attitudes (Hwang & Kim, 2015) and empower them (Tajurrahim et al., 2020). People desire to form relationships with others. Being accepted by others and receiving positive feedback from members of mobile social media may increase a user's sense of belonging to groups, and may stimulate more interaction with others and the development of new relationships (Ma & Chan, 2014). Fulfilled needs influence users’ emotional and psychological states regarding social media platforms, which consequently affects users’ allocation of cognition and attitude toward these platforms (Fedorikhin et al., 2008).

The attachment motivation construct has received some attention in the marketing literature (e.g., Chen, 2014; Ma & Chan, 2014).

For example, Chen (2014) found that Facebook use could fulfill users’ needs for interpersonal relationships and increase users’ attachment to the platform. Consequently, users had a positive attitude toward Facebook and had intentions to continue using it in the future (Chen, 2014). In the current study's mobile social media context, we posit that a high level of attachment to mobile social media will motivate users to form a positive attitude toward it. Therefore, we propose the following hypothesis:

H6. Attachment motivation is positively related to attitude toward mobile social media.

3.2.4 | Attitude and outcome behavior

We adapt Ajzen's (1991) definition of attitude to our study's context and define it as an individual's positive or negative feelings about using mobile social media. According to the TAM (Davis, 1986; Davis et al., 1989) and theory of planned behavior (Fishbein & Ajzen, 1975), attitudes exert a positive effect on behavioral use intention and users’ consequent actions.

The literature on social media is consistent with these views. Ha et al. (2015) focused on Facebook and KakaoTalk use in Korea to shed light on the significant impact of users’ attitudes toward mobile social media on their actual use behavior. Bailey et al. (2018) suggested that young Latin American users’ attitudes toward social media were positively related to their active social media behaviors. In our study, we suggest that users’ attitudes toward mobile social media will prompt them to spend more time on mobile social media. Therefore, we propose the following hypothesis:

H7. Attitude toward mobile social media is positively related to the actual use of mobile social media.

3.2.5 | Heterogeneity and international market segmentation

The heterogeneity of customers’ needs and preferences is the driving force behind market segmentation (Floh et al., 2014; Kim et al., 2020). Considerable heterogeneity characterizes international markets, so it is critical to identify similar underlying behavioral patterns in this context. Global users may have similar needs and preferences for mobile social media, regardless of the country in which they live. Thus, a post hoc segmentation method can be effectively used to conduct international microsegmentation (Wedel & Kamakura, 2000). Segmentation is particularly important in the development and implementation of successful global marketing strategies (Olsen et al., 2009; Walters, 1997).

Previous studies have highlighted the role of customer heterogeneity in the marketing domain (Chocarro et al., 2015; Floh et al., 2014; Wamba et al., 2017). For example, Wamba et al. (2017) assessed unobserved heterogeneity in the social media market, and

segmented users from five countries based on their responses. Their findings demonstrated that users' adoption behaviors and demographic characteristics were different in distinct segments. Thus, explaining users' behavioral differences in connection with their specific profiles, such as their demographics and culture, can help determine the characteristics that describe each of the revealed classes and manage users effectively (Chocarro et al., 2015).

Users' motives and behavioral patterns differ across segments, which is associated with users' demographic characteristics and cultural values. Cultural differences reflect the variation in values, attitudes, and behaviors that people share in society (Bond, 2004). Researchers have developed several frameworks to explain cross-cultural variation (e.g., Hofstede, 1980; Hofstede et al., 2010; House et al., 2004; Inglehart, 1997; Schwartz, 1992). The current study relies on Hofstede's cultural dimensions because of their widespread use and relevance in cross-cultural studies on social media (Abbas & Mesch, 2015; Gao et al., 2013; Hoehle et al., 2015; Ifinedo, 2016; Jackson & Wang, 2013) and appeal to academics and practitioners (de Mooij & Hofstede, 2010). Thus, we suggest that users in each segment have specific demographic characteristics and cultural values, and have distinct behavioral patterns when using mobile social media. Therefore, we propose the following hypothesis:

H8. Users' motivation, social influence, attitude toward mobile social media, and actual use behavior heterogeneity are associated with the demographic and cultural characteristics of the resulting international segments.

4 | METHODS

4.1 | Sampling and respondents' demographic characteristics

We selected mainland China and the United States for three reasons. First, both countries have a high penetration of mobile social media (71% in China and 61% in the United States) (We are Social & Hootsuite, 2019). Second, these two countries are profoundly different in their cultural value orientation (Hofstede, 2001). Third, some of their characteristics, such as their diverse and multicultural populations, indicate a high probability of the existence of unobserved customer heterogeneity. Quota sampling was applied to select survey participants in both countries because a sampling frame was unavailable, and this approach can provide a representative sample of various subgroups within a population (Babin & Zikmund, 2015). We controlled the proportions of age and sex intervals to resemble the countries' populations. We targeted Chinese and American users who had used mobile social media in the last six months.

Table 2 presents the demographic information of the 844 respondents who completed the questionnaire. The sample was quite balanced in terms of sex (53% males, 47% females) and nationality

TABLE 2 Descriptive analysis of categorical variables of the global model ($n = 844$)

Demographic variables	Categories	Frequency	Percentage
Sex	Female	393	47%
	Male	451	53%
Age	24-	210	25%
	25-30	262	31%
	31-35	213	25%
	36-40	107	13%
	41+	52	6%
Education	High school and below	112	13%
	Community college	132	16%
	Bachelors' degree	507	60%
	Masters' degree and above	93	11%
Nationality	China	420	49.76%
	United States	424	50.24%
Living area	Large cities	279	33%
	Medium-size cities	238	28%
	Small cities/rural area	327	39%

(49.76% Chinese, 50.24% Americans). Approximately 81% of the respondents were young, and 87% had higher education. Regarding location size, there are different definitions of city sizes and boundaries between cities and rural areas. To enhance comparability between Chinese and American locations, we defined the size of the location using the percentage of a location's population compared to the country's total population. Locations containing the highest 5% of the country's population were defined as large cities, locations containing the top 5% to the top 30% of the country's population were defined as medium cities, and the remaining locations were considered as small cities and rural areas.

4.2 | Questionnaire development, pretest, and data collection

We designed a four-section questionnaire to collect data from mainland China and the United States. This instrument was first developed in English and translated into simplified Chinese. A back-translation technique (from English to Chinese and back to English) was applied by third-party professionals to avoid linguistic biases (Jarvis et al., 2003). The first section inquired about aspects of actual use behavior, such as whether users had used social media on a smartphone during the last six months, the most used types of mobile social media, frequency of use, and the purpose of use. The second section explored the factors that drove users' actual use behavior. The third section measured users' cultural values, and the last section asked for users' demographic information.

To check the content validity and accuracy of the questions and its measures, we conducted qualitative and quantitative pretests before formally collecting data. We first asked for qualitative feedback and suggestions from various marketing professors, and then pretested the administration of the pretest with 30 mobile social media users. After some modifications, we conducted a quantitative pretest among 200 users by distributing a survey on several popular mobile social media applications in China, such as WeChat, QQ, and Sina Weibo.

After the pretests, we contracted an online panel company, Wenjuanxing, to create and distribute the questionnaire among Chinese respondents. Data collection began on January 30, 2019, and 420 valid responses were received in one week. All respondents were of Chinese nationality and, as requested, had used social media on a smartphone during the last six months. To collect the American sample, we created a questionnaire in Qualtrics and distributed it through Amazon Mturk. Data collection began on February 18, 2019, and we received 424 valid responses over two months. All respondents were of American nationality and had also accessed social media on smartphones during the last six months.

We used chi-square tests to verify whether there were significant differences with respect to age and sex between the two country groups (Hair et al., 2013). The p-values of the age interval and sex of the two countries were 0.719 and 0.484, respectively, implying no significant differences.

4.3 | Measurement of the variables

All constructs, except for actual use, which was measured with a single item, were operationalized using three items. Seven-point Likert scales ranging from “strongly disagree” (1) to “strongly agree” (7) were developed to measure each item. To measure *perceived enjoyment* (see Appendix 1 for the specific wording of the items in each construct), we focused on the pleasure that the users’ obtained from mobile social media. Two of the items were adapted from Zhou and Lu (2011). Consistent with Rauniar et al. (2014) and Strader et al. (2007), the *perceived usefulness* items explored the consumers’ perceptions of the effectiveness of mobile social media. *Perceived ease of use* items measured the extent to which it was easy to use mobile social media, and two of the items were adapted from Wamba et al. (2017). The fourth item in the scale (PEOU4) was reverse-coded in the database.

Subjective norms measured the influence received from influential people, and two items were adapted from Al-Debei et al. (2013). *Referent network size* captured the influence of social circle size, and we adapted two items from Zhou and Lu (2011). *Attachment motivation* reflected the extent to which users were emotionally connected with their social relationships through mobile social media, and one of the items was adapted from Chen (2014), while the other two were self-developed from the construct’s definition.

The three *attitude* items examined users’ feelings about mobile social media applications, and two of the items were adapted from

Chen (2014). Finally, *actual use* was a manifest variable adapted from Rauniar et al. (2014) to measure the hours that users spent daily on mobile social media.

Concerning the variables used to profile the international segments, *collectivism* examined the degree of the users’ feeling of belongingness to a group, and two of the items were adapted from Omoush et al. (2012) and Hoehle et al. (2015). Based on Hofstede’s conceptualizations, *power distance* items examined the degree of acceptance of inequalities among people; the items’ specific wording relied on Li et al. (2009). *Masculinity* examined whether competition, achievement, and success motivated people, while *uncertainty avoidance* measured users’ reactions to ambiguous or unknown situations. The last items of these two variables (MF3 and UA3 in Appendix 1) were adapted from Li et al. (2009), while the rest were self-developed.

To prevent and detect common method bias, we applied ex ante approaches in the research design stage (procedural remedies in designing and administering the questionnaire), while ex post approaches (statistical analyses) were implemented after the research was conducted (Chang et al., 2010; Podsakoff et al., 2003, 2012). Regarding the procedural remedies, to diminish social desirability, threats to self-esteem, and defensiveness (MacKenzie & Podsakoff, 2012; Podsakoff et al., 2003, 2012), we first assured that our survey was anonymous and there were no correct/incorrect answers. Second, to enhance the feeling of altruism (MacKenzie & Podsakoff, 2012; Podsakoff et al., 2012), we emphasized the importance of the participants’ opinions. Third, we randomized the order of appearance of the items in the questionnaire (Podsakoff et al., 2003, 2012). Regarding the statistical analyses, empirical evidence has indicated that this approach can detect biasing levels of common method variance under conditions usually found in survey-based marketing research (Fuller et al., 2016). We performed two Harman’s single factor tests for the Chinese and American data. The unrotated main factor from all the substantive items explained 21% of the total variance in the Chinese dataset and 34% in the American dataset; therefore, common method bias was unlikely to be present in our data (Fuller et al., 2016).

4.4 | Data analysis

We applied PLS-SEM to empirically test our model (R package *plspm*). PLS-SEM has several benefits, such as its high statistical power and flexible assumptions regarding model specification and data (Hair et al., 2011). Moreover, as PLS-SEM integrates the response-based unit segmentation REBUS-PLS algorithm (Vinzi et al., 2008), this allowed us to detect local models with better performance and to conduct post hoc segmentation. The REBUS algorithm was first used to estimate a global model (GM) with all observations ($n = 844$). Then, after the communality and structural residuals of each class from the GM were obtained, a hierarchical cluster analysis of the computed residuals from both the

measurement and structural models was performed to obtain the number of classes (Vinzi et al., 2010). We obtained three local models (LM1, LM2, and LM3) and estimated their parameters. The differences between the three classes were used to profile the resulting international segments.

5 | RESULTS

5.1 | Reliability and validity

Before testing our research hypotheses, we studied the measurement model in terms of item and construct reliability and convergent and discriminant validity. First, the factor loadings and descriptive statistics for all items are as shown in Table 3, and the factor loading of most items reaches the 0.7 threshold (Sanchez, 2013). The exceptions are PEOU2 in GM, LM1, LM2, and LM3; PEOU4 in LM3; and SN3 in GM, LM1, and LM3, although they are still over 0.5 (Sanchez, 2013) and have suitable construct reliability and validity, as explained below. Second, construct reliability was assessed in terms of composite reliability (CR; see Table 3). CR is greater than the 0.7 threshold (Hair et al., 2013) for all constructs and models except for perceived usefulness (PU) (0.65) and attachment motivation (AM) (0.69) in one of the local models (LM1). Third, with respect to convergent validity, we checked the average variance extracted (AVE) of the constructs. This is well above the cutoff point of 0.5 (Hair et al., 2013) for all constructs (see Table 3). Finally, when testing discriminant validity, the square root of the AVE of each construct should be higher than its correlations with other constructs (Hair et al., 2013), as is the case in the GM and the three local models (see Table 4). Overall, the results show that the items and constructs used in the GM and local models have been measured with an acceptable degree of reliability and validity, similar to most of the empirical research on international marketing.

5.2 | Global model results

The results of the structural part of the GM, based on all observations ($n = 844$), reveal a significant positive relationship between most explanatory constructs and attitude: perceived enjoyment ($\beta = 0.283, p < 0.001$), perceived usefulness ($\beta = 0.343, p < 0.001$), perceived ease of use ($\beta = 0.131, p < 0.001$), referent network size ($\beta = 0.067, p < 0.05$), and attachment motivation ($\beta = 0.128, p < 0.001$) (see Table 5, column 3). Thus, H1, H2, H3, H5, and H6 are empirically supported, while H4, which connects subjective norms and attitude, is not supported. Moreover, the relationship between attitude and actual use is also positively significant ($\beta = 0.172, p < 0.001$). Thus, H7 is also empirically supported. The R-squared values for attitude and actual use are 0.572 and 0.003, respectively.

5.3 | Local model results

We applied the REBUS-PLS (Vinzi et al., 2008) response-based clustering technique to group users automatically into segments, and obtained three local models, which we named LM1, LM2, and LM3. The results from the local models reveal that the determinants of attitude toward mobile social media vary across segments (see Table 5, columns four-six).

In LM1, only three factors are significantly related to attitude: perceived enjoyment ($\beta = 0.306, p < 0.001$), perceived usefulness ($\beta = 0.356, p < 0.001$), and attachment motivation ($\beta = 0.143, p < 0.05$). Thus, H1, H2, and H6 are empirically supported. Attitude also has a significant relationship with actual use ($\beta = 0.262, p < 0.001$), providing empirical support for H7. Respondents in this segment clearly know their purpose for using mobile social media, and their attitude does not change based on others' opinions, the herd effect, or ease of use. Thus, we labeled this segment as "usage goal experts."

In LM2, the significant drivers of attitudes are perceived enjoyment ($\beta = 0.150, p < 0.01$), perceived usefulness ($\beta = 0.464, p < 0.001$), perceived ease of use ($\beta = 0.122, p < 0.01$), referent network size ($\beta = 0.127, p < .01$), and attachment motivation ($\beta = 0.133, p < 0.01$). Therefore, H1, H2, H3, H5, and H6 are supported. In addition, the relationship between attitude and actual use is also significant ($\beta = 0.541, p < 0.001$), which empirically supports H7. Respondents in this segment are highly oriented toward the practicality and enjoyment of social media platforms, and their attitude toward mobile social platforms is not affected by perceived social pressure from others. Therefore, we labeled this segment "determined pragmatists."

In LM3, most factors are positively related to attitude: perceived enjoyment ($\beta = 0.389, p < 0.001$), perceived usefulness ($\beta = 0.179, p < .01$), perceived ease of use ($\beta = 0.156, p < 0.001$), subjective norms ($\beta = 0.200, p < 0.001$), and attachment motivation ($\beta = 0.175, p < 0.01$). Therefore, H1, H2, H3, H4, and H6 are supported. Attitude is also a significant determinant of actual use ($\beta = 0.707, p < 0.001$). Thus, H7 is supported. Respondents in this segment consider both the practicality and enjoyment of using social media platforms. However, the regression weight of perceived enjoyment peaks. In addition, these users are the only users who are influenced by subjective norms. Influential people exert psychological pressure on attitudes toward the use of new technologies, such as mobile social media. Consequently, we labeled this segment "pressured hedonists."

5.4 | International mobile social media user segments

5.4.1 | Demographic characteristics

We conducted chi-squared tests to examine whether there were significant differences in the demographic variables among the three

TABLE 3 Mean, standard deviations (SD) and factor loadings

Variable	Items	GM		LM1		LM2		LM3		GM		LM1		LM2		LM3		AVE			
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD				
PE	PE1	5.33	1.32	5.36	1.42	5.44	1.23	5.13	1.36	0.88	0.86	0.91	0.86	0.81	0.76	0.85	0.78	0.73	0.68	0.69	
	PE2	4.46	1.53	4.59	1.67	4.48	1.50	4.34	1.46	0.81	0.77	0.85	0.79	0.85	0.79	0.85	0.79	0.85	0.79	0.69	
	PE3	5.39	1.33	5.53	1.35	5.44	1.28	5.20	1.38	0.87	0.84	0.89	0.85	0.85	0.85	0.89	0.85	0.85	0.79	0.69	
PU	PU1	5.75	1.30	5.98	1.26	5.65	1.31	5.71	1.30	0.84	0.79	0.87	0.84	0.73	0.65	0.77	0.74	0.65	0.59	0.65	
	PU2	5.48	1.31	5.72	1.27	5.50	1.30	5.27	1.34	0.80	0.78	0.81	0.81	0.81	0.81	0.81	0.81	0.81	0.81	0.65	
	PU3	5.32	1.41	5.33	1.49	5.34	1.40	5.28	1.36	0.78	0.74	0.80	0.78	0.78	0.74	0.80	0.78	0.78	0.74	0.65	
PEOU	PEOU1	6.04	1.10	5.99	1.10	6.17	1.02	5.88	1.20	0.84	0.83	0.88	0.81	0.73	0.70	0.74	0.72	0.57	0.54	0.54	
	PEOU2	5.50	1.45	5.31	1.52	5.78	1.35	5.18	1.46	0.59	0.52	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.54	
	PEOU3	6.18	1.07	6.03	1.24	6.36	0.88	6.02	1.18	0.87	0.81	0.88	0.91	0.87	0.81	0.88	0.91	0.87	0.81	0.54	
	PEOU4	5.67	1.41	5.53	1.54	5.88	1.32	5.44	1.42	0.70	0.74	0.70	0.58	0.74	0.70	0.58	0.58	0.58	0.58	0.54	
SN	SN1	4.63	1.70	5.07	1.48	4.35	1.79	4.74	1.63	0.92	0.90	0.92	0.92	0.80	0.71	0.84	0.77	0.70	0.63	0.74	0.65
	SN2	4.82	1.70	5.40	1.51	4.52	1.81	4.84	1.54	0.92	0.90	0.93	0.89	0.80	0.71	0.84	0.77	0.70	0.63	0.74	0.65
	SN3	4.88	1.77	5.13	1.74	4.60	1.85	5.14	1.59	0.63	0.51	0.71	0.55	0.80	0.71	0.84	0.77	0.70	0.63	0.74	0.65
RNS	RNS1	6.40	1.02	6.41	1.14	6.39	0.97	6.40	0.98	0.89	0.87	0.91	0.86	0.85	0.86	0.88	0.81	0.77	0.78	0.81	0.72
	RNS2	6.28	1.06	6.34	1.16	6.25	1.01	6.28	1.05	0.89	0.92	0.89	0.85	0.85	0.86	0.89	0.85	0.85	0.77	0.78	0.81
	RNS3	6.24	1.01	6.36	0.98	6.22	0.99	6.18	1.05	0.86	0.86	0.89	0.84	0.85	0.86	0.89	0.84	0.85	0.77	0.78	0.81
AM	AM1	5.10	1.56	5.30	1.57	5.04	1.54	5.06	1.58	0.84	0.81	0.87	0.81	0.76	0.69	0.80	0.73	0.67	0.62	0.72	0.64
	AM2	5.00	1.60	5.39	1.47	4.74	1.71	5.12	1.46	0.76	0.72	0.80	0.72	0.76	0.72	0.80	0.72	0.67	0.62	0.72	0.64
	AM3	4.97	1.41	5.25	1.36	4.88	1.43	4.90	1.39	0.86	0.81	0.87	0.87	0.76	0.72	0.80	0.72	0.67	0.62	0.72	0.64
ATT	ATT1	5.78	1.28	5.77	1.35	5.89	1.20	5.61	1.34	0.89	0.89	0.91	0.86	0.83	0.83	0.86	0.75	0.74	0.75	0.78	0.66
	ATT2	5.55	1.23	5.65	1.36	5.73	1.10	5.20	1.24	0.82	0.83	0.86	0.75	0.83	0.83	0.86	0.75	0.74	0.75	0.78	0.66
	ATT3	5.60	1.28	5.61	1.35	5.73	1.19	5.37	1.34	0.86	0.87	0.88	0.83	0.83	0.86	0.75	0.74	0.75	0.78	0.66	
AU	AU1	3.33	1.70	5.85	1.04	2.03	0.70	3.39	0.60	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

TABLE 4 Discriminant validity^a, correlations, and square roots of the average variance extracted (AVE)

	PE	PU	PEOU	SN	RNS	AM	ATT	AU
GM								
PE	0.85							
PU	0.64**	0.81						
PEOU	0.30**	0.32**	0.76					
SN	0.29**	0.43**	-0.02	0.84				
RNS	0.23**	0.38**	0.47**	0.27**	0.88			
AM	0.56**	0.67**	0.13**	0.53**	0.30**	0.82		
ATT	0.64**	0.69**	0.37**	0.34**	0.37**	0.57**	0.86	
AU	0.14**	0.23**	-0.05	0.30**	0.14**	0.25**	0.17**	1.00
LM1								
PE	0.82							
PU	0.65**	0.77						
PEOU	0.43**	0.46**	0.74					
SN	0.25**	0.42**	0.11	0.79				
RNS	0.20**	0.44**	0.51**	0.30**	0.88			
AM	0.56**	0.66**	0.31**	0.45**	0.32**	0.78		
ATT	0.65**	0.70**	0.40**	0.35**	0.36**	0.60**	0.86	
AU	0.09	0.23**	0.13	0.14*	0.20**	0.09	0.26**	1.00
LM2								
PE	0.88							
PU	0.69**	0.83						
PEOU	0.28**	0.30**	0.77					
SN	0.34**	0.45**	-0.04	0.86				
RNS	0.29**	0.41**	0.49**	0.28**	0.90			
AM	0.59**	0.66**	0.11*	0.56**	0.32**	0.85		
ATT	0.61**	0.73**	0.38**	0.33**	0.45**	0.56**	0.88	
AU	0.37**	0.46**	0.12*	0.34**	0.33**	0.42**	0.54**	1.00
LM3								
PE	0.83							
PU	0.56**	0.81						
PEOU	0.22**	0.29**	0.73					
SN	0.27**	0.40**	0.05	0.80				
RNS	0.14*	0.28**	0.46**	0.26**	0.85			
AM	0.52**	0.70**	0.13*	0.51**	0.24**	0.80		
ATT	0.67**	0.64**	0.32**	0.47**	0.27**	0.62**	0.81	
AU	0.45**	0.42**	0.25**	0.31**	0.17**	0.45**	0.71**	1.00
AM	0.52**	0.70**	0.13*	0.51**	0.24**	0.80		
ATT	0.67**	0.64**	0.32**	0.47**	0.27**	0.62**	0.81	
AU	0.45**	0.42**	0.25**	0.31**	0.17**	0.45**	0.71**	1.00

^aDiagonal values in bold are the square roots of the variance shared between the constructs and their measures.

** $p < 0.01$; * $p < 0.05$

segments (see Table 6). Sex ($p < 0.05$), age ($p < 0.001$), nationality ($p < 0.001$), and geographic location ($p < 0.001$) are significantly different across segments, while education is not ($p < 0.885$). The most used mobile social media applications are also significantly different

across the three segments (WeChat: $p < 0.001$, Facebook: $p < 0.01$, QQ: $p < 0.001$, and YouTube: $p < 0.001$).

In segment 1 ("usage goal experts"), most respondents are Chinese ($n = 132:66\%$), female ($n = 108:54\%$), aged between 25–30 years

Independent variables	Dependent variables	GM	LM1	LM2	LM3
PE	ATT	0.283***	0.306***	0.150**	0.389***
PU		0.343***	0.356***	0.464***	0.179**
PEOU		0.131***	0.017 ns	0.122**	0.156***
SN		0.026 ns	0.037 ns	-0.037 ns	0.200***
RNS		0.067*	0.075 ns	0.127**	-0.007 ns
AM		0.128***	0.143*	0.133**	0.175**
ATT	AU	0.172***	0.262***	0.541***	0.707***
R square (%)	ATT	0.572	0.580	0.595	0.627
	AU	0.030	0.069	0.293	0.499

Note: ns: not significant.

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

TABLE 5 Coefficients of determination, R square, and goodness of fit

TABLE 6 Descriptive statistics and significance of local model categorical and continuous variables

Variable	Categories	Relative frequency per category (%)			χ^2 statistics	p-value			
		LM1 (n = 200)	LM2 (n = 399)	LM3 (n = 245)					
Sex	Female	54%*	42%*	48%	8.25	0.020			
	Male	46%*	58%*	52%					
Age	24-	33%*	18%**	29%	52.27	<0.001			
	25-30	37%	26%*	34%					
	31-35	23%	30%*	20%					
	36-40	7%*	16%	12%					
	41+	1%**	10%**	5%					
Education	High school and below	12%	15%	11%	2.35	0.885			
	Community college	15%	16%	16%					
	Bachelor's degree	62%	58%	62%					
	Master's degree and above	11%	11%	11%					
Country	China	66%***	36%***	60%**	62.62	<0.001			
	United States	34%***	64%***	40%**					
Geographic location	Large city	42%*	26%**	37%	21.77	<0.001			
	Medium city	29%	28%	28%					
	Small city/rural area	30%**	46%**	35%					
Cultural dimensions		Mean	SD	Mean	SD	Mean	SD	Kruskal-Wallis	p-value
	Collectivism	0.28	1.29	-0.13	1.31	-0.02	1.13	12.03	<0.01
	Power distance	-0.11	1.15	0.09	1.27	-0.05	1.10	4.33	0.115
	Masculinity	0.20	1.22	-0.12	1.35	0.04	1.33	8.22	<0.05
	Uncertainty avoidance	0.02	1.17	-0.10	1.07	0.15	1.09	8.81	<0.05

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$ represent the significance level of the test of given proportions, in which the proportions in each cluster are compared with the corresponding proportions in the total sample.

($n = 73:37\%$), and live in large Chinese cities ($n = 83:42\%$). WeChat is the most used mobile social media application ($n = 131:66\%$). In segment 2 ("determined pragmatists"), most respondents are American ($n = 257:64\%$), male ($n = 232:58\%$), aged between 31-35 years ($n = 118:30\%$), and live in small cities or rural areas ($n = 183:46\%$).

Facebook is the most popular mobile social media platform in this group ($n = 200:50\%$). In segment 3 ("pressured hedonists"), most respondents are Chinese ($n = 146:60\%$), male ($n = 127:52\%$), aged between 25-30 years ($n = 84:34\%$), and live in large Chinese cities ($n = 91:37\%$). WeChat is the most used application in this segment ($n = 144:59\%$).

5.4.2 | Cultural characteristics

We performed statistical tests to examine whether the three segments had significantly different cultural orientations (see Table 6). We first estimated the mean and standard deviation of the standardized factor scores of each cultural dimension in each of the three segments. Then, given that the variables were not normally distributed, we conducted the Kruskal–Wallis test and found heteroscedasticity across the groups. The results show that, except for power distance ($p = 0.115$), the cultural dimensions are significantly different across the three segments: collectivism ($p < 0.01$), masculinity ($p < 0.05$), and uncertainty avoidance ($p < 0.05$). According to the mean of the cultural values, respondents in segment 1 (“usage goal experts”) have the highest collectivism and masculinity scores. Therefore, they may perceive a higher sense of belonging to a group and may pay more attention to competition and achievements (Hofstede, 2001). In segment 2 (“determined pragmatists”), respondents are more individualistic, feminine-oriented, and tolerant toward uncertainty. Consequently, they may only look after themselves and their direct families, pay substantial attention to their quality of life, and be less influenced by ambiguous or unknown situations (Hofstede, 2001). Respondents in segment 3 (“pressured hedonists”) have the highest degree of uncertainty avoidance, meaning that ambiguity or unknown situations may cause them anxiety (Hofstede, 2001).

6 | DISCUSSION

6.1 | General discussion

This study identifies the determinants of attitude toward mobile social media, confirms the significant role played by attitude as a driver of actual use behavior, assesses users’ heterogeneity, and conducts an international microsegmentation of mobile social media users. Our hybrid research model integrates factors based on the TAM, motivation theory, and social influence theory. We tested the hypothesized relationships in the GM and the three local models. The findings show that users’ attitude toward mobile social media is influenced by motivational and social influence factors. As expected, users’ attitude results in actual use behavior. Nevertheless, some determinants differ across the segments because of the users’ different demographic characteristics and cultural value orientations.

First, regarding motivational factors, the results highlight perceived usefulness as the most influential factor (in the GM and two local models) that affects users’ attitude toward mobile social media. This finding is in line with the earlier correlational studies by Bailey et al. (2018) and Lin and Kim (2016), who showed that users’ positive attitude toward social media (Bailey et al., 2018) and social media advertisements (Lin & Kim, 2016) were mainly due to users’ beliefs in their usefulness. Moreover, users have other significant motivations, and aim to enjoy using mobile social platforms. This finding is in line with Bailey et al. (2018) and Chen (2014), who pointed out users’ need for entertainment on social media platforms. The more

relaxed and pleasant the user experience is on these platforms, the more positive their attitude toward the platforms will be (Bailey et al., 2018; Chen, 2014). Users also pay attention to whether these platforms are easy to use (in the GM and two local models), which is also in line with Lin and Kim (2016).

Second, users’ attitude toward mobile social media platforms are also affected by social influence factors. However, subjective norms are not a significant determinant of users’ attitudes toward platforms (in the GM and two local models). This result is inconsistent with the studies that suggest that users’ attitudes toward technology will be positively influenced by people who are important to them (Chen, 2014; Im & Ha, 2013). This may be because users currently have more channels (e.g., online forums, online discussion groups, and online brand communities) from which to gather information about technological applications. The increased number of online reference groups may weaken the significance of the opinions from peers or important persons during the behavioral process. Users will form a positive attitude toward mobile social media platforms if they are popular in their social circle (in the GM and one local model). Regarding the referent network size, we found limited empirical evidence on the relationship between users’ social circle size and attitude (in the GM and one of the local models). In relation to attachment motivation, this is the most important determinant of attitude toward mobile social media within this second group of factors. Users expect to improve their relationships with others through mobile social media, which is consistent with Ma and Chan (2014) and Chen (2014).

Third, users’ attitude toward mobile social media is a critical factor that stimulates usage. This result is in line with Omoush et al. (2012) and Bailey et al. (2018). The more favorable users’ attitude toward a social media platform is, the more likely they are to employ it. Fourth, when taken together, the varying results for the local models suggest that international users with different demographics and cultural characteristics may have different use motivations and technology adoption behaviors.

Finally, our results also show that the three segments based on respondents’ behavioral patterns (“usage goal experts,” “determined pragmatists,” and “pressured hedonists”) are heterogeneous. Thus, assuming that mobile social media users are homogeneous may provide a misleading view of their real behavior. Overall, our findings are consistent with Wamba et al. (2017), who suggest that social media users are not homogenous and that the effects of motivators differ in distinct user segments that have different demographic characteristics.

6.2 | Implications for theory

Our findings have important implications for theory. First, this study enhances the understanding of attitude toward mobile social media and actual use behavior by integrating into a hybrid model factor related to the TAM, motivation theory, and social influence theory. The previous literature (a) has not accounted, in a single model, for all the

theoretical perspectives and factors that we combine herein (e.g., Bailey et al., 2018; Ha et al., 2015); (b) has not paid much attention to the role of attitude toward mobile social media to explain actual use behavior (e.g., Assimakopoulos et al., 2017; Guenzi & Nijssen, 2020); and (c) neglects the referent network size as a relevant driver of users' attitudes toward mobile social media (e.g., Hong et al., 2017; Zhang et al., 2017). Our study is also unique in revealing that motivation theory may have more explanatory power on attitude and mobile social media use than social influence theory. In other words, based on our findings, we can state that although both motivation and social influences affect attitude toward mobile social media, motivation plays a more important role. In addition, we can confirm, across different populations, that attitude is an important component in the behavioral process of mobile social media use.

Second, our study also contributes to the literature on international market segmentation by highlighting the importance of heterogeneity in international microsegmentation. This study provides strong support for the necessity of conducting international microsegmentation at the individual level in the research domain of mobile social media, and paves the way by developing new items to operationalize some of our constructs (in particular, some dimensions of cultural value orientation) and by using them at the individual level. Most of the previous research on international marketing and social media has used Hofstede's scores at the country level to operationalize culture (e.g., Amaro & Duarte, 2017; Sheldon et al., 2017), which is misleading in research contexts such as social media, where there are more users who are both of younger age and frequent users of ICT (Bailey et al., 2018).

6.3 | Implications for practice

From a practical perspective, our findings have important implications for mobile social media application developers and international marketing practitioners. Given that perceived enjoyment, perceived usefulness, and attachment motivation are three significant drivers of attitude toward mobile social media in the GM and three local models, application developers can enhance users' attitude by improving the entertainment, practical, and social functionality of their applications. Moreover, our results also show that generally, ease of use positively impacts users' attitude toward mobile social media. Thus, mobile social media developers should pay attention to applications' interface design to adapt to aspects such as the limited screen size of mobile devices to better integrate social media applications with smartphone technology.

Our empirical findings revealed three user segments with significant differences in behavioral patterns, demographic characteristics, and cultural values. Therefore, international marketing practitioners should avoid designing international marketing strategies that rely exclusively on a priori segmentation at the country level. Instead, they should conduct international segmentation based on users' behavioral patterns and offer customized mobile social media services.

In the "usage goal experts" segment, considering the significant impact of perceived usefulness, perceived enjoyment, and attachment motivation, marketers should strengthen the entertainment, practical, and social functionality of their mobile social media applications. Concerning the "determined pragmatists" segment, since perceived usefulness is the most influential factor, and that the coefficients of perceived usefulness and referent network size are the highest among the three segments, the most effective marketing strategies would be to improve the practicality of applications and make use of the herd effect. Finally, regarding the "pressured hedonists" segment, perceived enjoyment is the most important factor, while the impact of attachment motivation and subjective norms are the highest among the three segments. Therefore, firms targeting this segment should consider increasing the entertainment functionality of the application, apart from relying on influencers to strengthen users' attitude.

7 | FUTURE RESEARCH AND LIMITATIONS

We follow the theory-context-characteristics-methodology framework (Paul & Rosado-Serrano, 2019) to propose an agenda for future research. First, in terms of theory, our study included several factors from three relevant theoretical lenses (the TAM, motivation theory, and social influence theory). However, other theories and factors could explain attitude toward mobile social media and actual use and complete our model specification. In particular, perceived playfulness (Wamba et al., 2017) and perceived utility (Lacka & Chong, 2016) may be additional motivational factors, and informational social influence and normative social influence (Li, 2013) could be considered from a social influence theory perspective. In addition, attitude is the mechanism connecting motivational and social influence factors to mobile social media use. We explored its mediating role and found mixed results (the mediating role of attitude toward mobile social media varies across segments). Therefore, future research should study its mediating role in detail, and consider other potential mediators such as behavioral intention.

Second, in terms of context, our study discusses mobile social media use behavior in general. However, there are different types of mobile social media platforms that are used based on their distinct functionalities (e.g., YouTube for videos, Instagram for photos, and WhatsApp for messages). Therefore, there is also heterogeneity across mobile social media platforms (Ju et al., 2021). Future studies could explore attitudes toward mobile social media and use behavior across different types of platforms. In addition, despite the emphasis on the impact of the COVID-19 pandemic on customers' online behavior (Karpen & Conduit, 2020), few efforts have been made to study mobile social media use during the pandemic. Since people may have different motivations for using mobile social media in unusual situations, future research could replicate our study in light of the COVID-19 context to explore the potential differences in users' behavioral patterns.

Third, regarding characteristics, we obtained empirical evidence only from China and the United States. Thus, researchers need to be cautious when generalizing the results to populations from other countries. Scholars are encouraged to collect samples from other countries and regions such as Europe, Oceania, the Middle East, Africa, and South America to study whether our results hold, and whether the international segments discovered herein exist globally.

Fourth, concerning methods, we utilized PLS-SEM because it provided us with the option to use the REBUS-PLS algorithm (Vinzi et al., 2008) to conduct international microsegmentation. However, the alternative SEM estimation approach—covariance-based structural equation modeling (CB-SEM)—can also be used to estimate our conceptual model. Finally, future mobile social media studies can be advanced by comparing results from a priori and post hoc international microsegmentations of behavioral patterns and cultural and demographic characteristics.

8 | CONCLUSION

By combining three theoretical perspectives (TAM, motivation theory, and social influence theory), we identify the determinants of mobile social media use and conduct post hoc international microsegmentation of behavioral patterns using a sample of 844 Chinese and American users. Our findings suggest that motivation theory has more explanatory power for mobile social media use than social influence theory. In addition, three segments emerged from the microsegmentation of mobile social media users (“usage goal experts,” “determined pragmatists,” and “pressured hedonists”), which significantly differ in their behavioral patterns, cultural value orientations, and demographic characteristics.

CONFLICT OF INTEREST

The authors have no conflict of interest.

DATA AVAILABILITY STATEMENT

Data available from the authors upon request.

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APPENDIX 1. Survey instrument

Constructs	Measurement items	Reference
Perceived enjoyment (PE)	PE1: I find using social media on my cell phone a pleasant experience.	Self-developed
	PE2: I find using social media on my cell phone very exciting.	Adapted from (Zhou & Lu, 2011)
	PE3: Using social media on my cell phone is fun.	Adapted from (Zhou & Lu, 2011)
Perceived usefulness (PU)	PU1: Social media on my cell phone are useful in my personal life.	Adapted from (Rauniar et al., 2014)
	PU2: By using social media on my cell phone I have more ways of expressing myself.	Self-developed
	PU3: Using social media on cell phone improves my communication with others.	Adapted from (Strader et al., 2007)
Perceived ease of use (PEOU)	PEOU1: It is easy to use the main social media applications and tools on my cell phone (for example, to share messages and videos).	Self-developed
	PEOU2: Using social media on my cell phone does not require much mental effort.	Adapted from (Wamba et al., 2017)
	PEOU3: It is easy to use social media on the cell phone.	Adapted from (Wamba et al., 2017)
	PEOU4: It takes a long time to understand most social media functions on a cell phone.	Self-developed
Subjective norms (SN)	SN1: People who influence my behavior think I should use social media on my cell phone.	Adapted from (Al-Debei et al., 2013)
	SN2: Those important to me think I should use social media on my cell phones.	Adapted from (Al-Debei et al., 2013)
	SN3: Society influences me to use social media on my cell phones.	Self-developed
Reference network size (RNS)	RNS1: Most of my friends use social media on their cell phones.	Adapted from (Zhou & Lu, 2011)
	RNS2: Most of my classmates or colleagues use social media on their cell phones.	Adapted from (Zhou & Lu, 2011)
	RNS3: Most of the people in my circle use social media on their cell phones.	Self-developed

Constructs	Measurement items	Reference
Attachment motivation (AM)	AM1: Using social media on my cell phone helps me feel closer to others.	Adapted from (Chen, 2014)
	AM2: I like my mobile social media followers to be interested in how I am and what I'm doing.	Self-developed
	AM3: I feel good when I find and follow other social media users on my cell phone.	Self-developed
Attitude (ATT)	ATT1: I am in favor of the use of social media on cell phones.	All of them are adapted from (Chen, 2014)
	ATT2: I think that users benefit from the possibility of accessing social media on cell phones.	
	ATT3: Using social media on cell phones is a good idea.	
Actual use (AU)	AU1: How many hours a day do you use social media on your cell phone?	Adapted from (Al-Debei et al., 2013)
Collectivism (IC)	IC1: I normally accept group decisions well although my personal opinion may be different.	Adapted from (Omoush et al., 2012)
	IC2: Being accepted as a member of a group is more important than having autonomy and independence.	Adapted from (Hoehle et al., 2015)
	IC3: The opinions of other people frequently influence my intention to do something.	Self-developed
Power distance (PD)	PD1: Managers should make their decisions without consulting employees.	All of them are adapted from (Li et al., 2009)
	PD2: Employees should not question the decisions of their managers.	
	PD3: The existence of social inequalities is acceptable.	
Masculinity (MF)	MF1: Professional achievements are important and should be rewarded.	Self-developed
	MF2: I think one's professional career is as important as one's quality of life.	Self-developed
	MF3: In my opinion, some jobs are more suitable for a man than for a woman.	Adapted from (Li et al., 2009)
Uncertainty avoidance (UA)	UA1: I'm afraid of changes because I think that things could get worse.	Self-developed
	UA2: I'm afraid of trying new things.	Self-developed
	UA3: I feel uncomfortable in ambiguous situations and with unknown risks.	Adapted from (Li et al., 2009)

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A social media competitive intelligence framework for customer engagement prediction and decision support

Abstract

Social media competitive intelligence frameworks provide marketing practitioners with actionable knowledge and support decision-making. However, although the predictive validity and influence of the external environment are critically important for the framework, efforts to incorporate these elements into it are scarce. This study presents a refined social media competitive intelligence framework that incorporates the influence of the external environment and the phase to predict customer engagement. A case study is conducted to illustrate the implementation of the proposed framework. We collected tweets generated by 23 leading American catering brands before and during the COVID-19 pandemic. In the first phase, we used Amazon Comprehend and Latent Dirichlet allocation (LDA) to analyze sentiments and topics behind unstructured text data. In the second phase, we trained the classifiers using six machine learning algorithms to predict customer engagement. The results reveal that firms' topic patterns changed after the outbreak of the pandemic. Moreover, the influence of the predictors on customer engagement differed before and during the pandemic. The support vector machine (SVM) performs best in terms of accuracy and the C5.0 tree is a compromise approach between predictivity and interpretability.

Keywords: *Competitive intelligence, Customer engagement, Social media, COVID-19, Unstructured data, Machine learning*

A social media competitive intelligence framework for customer engagement prediction and decision support

1. Introduction

The concept of intelligence, as part of a marketing strategy, has been proposed as an effort to increase firms' competitiveness and strategic planning (Dishman & Calof, 2008). The explosion of social media data provides opportunities to gain competitive intelligence (He et al., 2017). Extracting intelligence from massive social media data creates value for firms (Erevelles et al., 2016; Ranjan & Foropon, 2021). Competitive intelligence not only empowers firms to identify current industrial changes in the environment (Wedel & Kannan, 2016), but also examine competitors' strengths, weaknesses, and strategies (Bose, 2008). Intelligence also contributes to trend forecasting (Wedel & Kannan, 2016), which guides firms in making the right decisions (Perez-Vega et al., 2021), especially during extreme events or crises (Stieglitz et al., 2017).

While a large amount of textual data in social media empowers competitive intelligence (He et al., 2013), it is only useful when internal insights are extracted (Berger et al., 2020). For this reason, researchers have established competitive intelligence frameworks that integrate various data analysis methods to guide marketers to gain competitive intelligence from social media data and for decision support (Dai et al., 2010; He et al., 2015). Through this framework, researchers have extracted various types of knowledge from unstructured social media data, including sentiments (He et al., 2016, 2017; He, Shen, et al., 2015; He, Wu, et al., 2015; Ibrahim & Wang, 2019; Zhan et al., 2021) and topics (He et al., 2013, 2017; Ibrahim & Wang, 2019; Zhan et al., 2021). However, several important research gaps remain in the literature on social

media competitive intelligence.

First, environmental uncertainty affects firms' decision-making and marketing strategies (Sharma et al., 2020). The outbreak of the COVID-19 pandemic represents one of the most significant environmental changes in modern marketing history (He & Harris, 2020). COVID-19 is an infectious disease caused by a newly discovered coronavirus identified in Wuhan (China) in December 2019 (WHO, 2020). The World Health Organization (WHO) declared COVID-19 a global pandemic on March 11, 2020 (WHO, 2020). During the pandemic, customer behavior has been fundamentally altered and many industries have been affected (Donthu & Gustafsson, 2020; Karpen & Conduit, 2020). For instance, in the catering industry, restaurants around the world are forced to close or shorten operating hours due to pandemic containment measures (Li et al., 2021). Competitive intelligence is especially important during crises. Competitive intelligence extracted from social media data, such as topics and sentiments, enables firms to learn how competitors change their strategies to engage with customers in social media during the crisis (Stieglitz et al., 2017), which guides firms in making the right decision to survive (Moe & Schweidel, 2017). Researchers have revealed the topic evolution of fortune CEOs in their tweets before and during the COVID-19 pandemic (Yadav et al., 2021). However, although firms' social media strategies are found to be altered due to environmental change (Yadav et al., 2021), current social media competitive intelligence frameworks assume that the data input in the framework is unchangeable. Therefore, limited knowledge is available regarding the impact of the external environment on firms' social media strategies.

Second, competitive intelligence incorporates information from a strategic perspective, allowing a company to predict what is going to happen in its competitive environment (Bose,

2008). Therefore, predictive validity should be critically important in the social media competitive intelligence framework. Predictive validity refers to the ability of the measured constructs to predict other constructs in the nomological network (Humphreys & Wang, 2018). Influenced by environmental uncertainty, customers increasingly engage in social media during the pandemic (Donthu & Gustafsson, 2020). Customer engagement in social media refers to customers' behavioral manifestations toward a brand or firm beyond purchasing (van Doorn et al., 2010). Interactions between firms and customers can be valuable in predicting future relationships, which enhances decision-making to increase customer engagement (Perez-Vega et al., 2021). Nevertheless, efforts to incorporate the prediction of customer engagement in the social media competitive intelligence framework are scarce. Existing studies on social media competitive intelligence use descriptive analysis to explore the relationships between firm-generated content and customer engagement (Ibrahim et al., 2017; Yost et al., 2021). Therefore, how to employ gained intelligence to predict customer engagement in social media remains unclear.

The research has two objectives. The first is to explore the impact of the external environment on firms' social media strategies. The second is to clarify how the gained competitive intelligence can be used to predict customer engagement in social media. To achieve these objectives, we first proposed a social media competitive intelligence framework by refining existing frameworks in the literature. In the proposed framework, we highlighted the impact of the external environment on the nature of data, apart from incorporating the prediction phase. We then used a case study of 23 leading catering brands in the United States to illustrate the implementation of the proposed framework.

This study makes both theoretical and practical contributions. From a theoretical perspective, this study contributes to the social media competitive intelligence literature by incorporating the impact of the external environment and prediction phase into the framework. This research bridges the social media competitive intelligence framework from the conceptual level to the operational level. From a practical perspective, our framework guides marketing practitioners to extract intelligence from social media and use the gained intelligence to predict customer engagement. Moreover, the empirical results of the case study reveal the specific sentiment and topic patterns of the main players in the American catering industry. Therefore, these results are valuable for marketing practitioners to analyze the evolutionary trends of sentiments and topics in the catering industry before and during the pandemic.

The remainder of this paper is organized as follows. In the second section, we review related studies. In the third section, we propose our social media competitive intelligence framework. In the fourth section, we illustrate the implementation of the proposed framework through a case study. In the fifth section, we discuss the results of this research and introduce their implications. In the last section, we introduce the limitations of this research and offer directions for future research.

2. Literature review

2.1. Social media competitive intelligence frameworks

Competitive intelligence is defined as “*a combination of defining, gathering, and analyzing intelligence about products, customers, competitors, and any aspect of the environment needed to support executives and managers in making strategic decisions for an organization*” (Dey et

al., 2011, p. 1). Many researchers have proposed the intelligence process under different labels, such as environmental scanning (Fahey et al., 1981), strategic intelligence (Montgomery & Weinberg, 1979), business intelligence (Cleland & King, 1975), and market intelligence (Maltz & Kohli, 1996). In the social media context, competitive intelligence is termed as social media intelligence (Zeng et al., 2010) or social media competitive intelligence (He et al., 2013; He, Shen, et al., 2015). In this research, we refer to competitive intelligence in the social media context as social media competitive intelligence.

Advances in information technology, especially social media, have empowered the benefits of competitive intelligence (Bose, 2008). The Internet and mobile technologies have driven the rise of social media, which provides platforms for information dissemination, content generation, and interactive communication (Ju et al., 2021; Zeng et al., 2010). Social media competitive intelligence analysis plays an important role in corporate decision-making (Holsapple et al., 2018; Stieglitz et al., 2014), which benefits firms by extracting the “wisdom of crowds” on the Internet (Zeng et al., 2010). Social media competitive intelligence helps firms extract business values from the huge amount of social media data and enhance their marketing performance (He et al., 2013; He, Shen, et al., 2015).

Researchers have proposed several frameworks to describe how to gain competitive intelligence and extract business value by mining social media data. To systematically review such studies, we searched for journal articles in ScienceDirect, Scopus, and Web of Science using the following keywords in the title, abstract, keywords, and full text of the articles: “social media analytics,” “social media competitive intelligence,” “social media business intelligence,” and “social media big data analysis.” Finally, we identified 10 relevant studies. Table 1

summarizes the objectives, industries, methods, and contributions of the studies. Studies that focus on social media competitive intelligence frameworks can be tracked to 2013 (see Table 1, column one).

Most studies focus on describing how to conduct a competitive analysis and convert data into actionable knowledge for decision-makers (He et al., 2013, 2017; He, Shen, et al., 2015; He, Wu, et al., 2015; Jimenez-Marquez et al., 2019). Few studies discuss the specific benefits empowered by competitive intelligence, including service (Ibrahim & Wang, 2019; Zhan et al., 2021), customer experiences (He et al., 2016), sales improvement (Yost et al., 2021), and promoted post detection (Arora et al., 2020) (see Table 1, column two). Retailing is the most investigated industry (see Table 1, column three). Twitter is the most investigated social media platform, and the samples were collected using the Application Programming Interface (API) of the Twitter Developer Platform (He et al., 2017; He, Shen, et al., 2015; He, Wu, et al., 2015; Ibrahim & Wang, 2019; Yost et al., 2021; Zhan et al., 2021) (see Table 1, column four). Sentiment analysis is the most commonly used text mining method to extract intelligence from unstructured data (He et al., 2017; He, Shen, et al., 2015; He, Wu, et al., 2015; Ibrahim & Wang, 2019; Jimenez-Marquez et al., 2019; Yost et al., 2021; Zhan et al., 2021), followed by topic/themes analysis (He et al., 2013, 2017; He, Shen, et al., 2015; Ibrahim & Wang, 2019; Yost et al., 2021; Zhan et al., 2021), concept maps (He et al., 2016, 2017; Zhan et al., 2021), and social network analysis (Ibrahim & Wang, 2019) (see Table 1, column five). The case study is the most used approach by researchers to demonstrate the implications of their proposed frameworks (He et al., 2013, 2016, 2017; He, Shen, et al., 2015; Jimenez-Marquez et al., 2019; Zhan et al., 2021) (see Table 1, column five). The findings of existing studies reveal that social

media competitive intelligence frameworks are effective in converting social media data into actionable knowledge. The extracted intelligence, such as sentiment and topics, can be used to enhance firms' competitiveness in the market (see Table 1, column six).

Nevertheless, in the reviewed literature, we failed to find a framework in which the impact of the external environment was highlighted, and the prediction phase was incorporated. On the one hand, current social media competitive intelligence frameworks tend to treat the nature of data as unchangeable. Researchers have found that, in comparison with the normal situation, the nature of social media data has changed after the COVID-19 pandemic (Yadav et al., 2021). On the other hand, the prediction phase in the current social media competitive intelligence framework is missing. The predictive function should be incorporated into the social media competitive intelligence framework as one of the important purposes of competitive analysis is to predict what is going to happen in the market (Bose, 2008).

(Insert Table 1 about here)

2.2. Social media competitive intelligence and customer engagement

Customer engagement has been discussed as an essential marketing outcome (Hollebeek et al., 2014; Pansari & Kumar, 2017). Engaged customers typically display greater brand loyalty (Algharabat et al., 2020; Kaur et al., 2020) and purchase intentions (Meire et al., 2019). Customer engagement is a value co-creation process that drives a firm's financial success (Kunz et al., 2017). Thus, firms seek ways to create lasting customer engagement in social media rather than merely enhancing short-term revenue (Schultz & Peltier, 2013).

Researchers have identified various factors that affect customer engagement in social media, including content format (e.g., Dhaoui & Webster, 2021; Moran et al., 2020), content types (e.g., Juntunen et al., 2020; Shahbaznezhad et al., 2021), sentiment of the content (e.g., Rietveld et al., 2020), topics extracted from the content (e.g., Jalali & Papatla, 2019; Zhang et al., 2017), and initiative character (e.g., Eigenraam et al., 2021; Meire et al., 2019). Moreover, researchers have found that firm-initiated activities can be modeled using machine learning systems to predict customer engagement behavior (Perez-Vega et al., 2021). Therefore, competitive intelligence derived from firm-generated content can be incorporated into the framework to predict customer engagement in social media.

3. The proposed framework

For the data to be useful, researchers and managers need a framework to measure, track, understand, and interpret the cause and consequences of marketplace behavior (Berger et al., 2020). Accordingly, this study proposes a framework that takes firm-generated social media data as inputs, integrates text mining methods to extract competitive intelligence, and employs the gained intelligence. In contrast to previous studies, apart from illustrating the process of converting unstructured social media data into competitive intelligence, our framework also illustrates how the gained intelligence can be used to predict customer engagement in social media, which further supports firms' decision-making.

In this section, we introduce our social media competitive intelligence framework, as shown in Fig.1. The proposed framework consists of two main phases. The first phase illustrates how to convert data into competitive intelligence. The second phase illustrates how to use the

gained intelligence for decision-making that predicts customer engagement in social media. Our framework relies on a series of information system technologies, including programming languages (e.g., Python and R), integrated development environments (IDEs), and cloud computing (e.g., Amazon AWS, Google Cloud, and Microsoft Azure).

(Insert Figure 1 about here)

The first phase starts with access to social media data. Analysts can first use an API to retrieve raw data from social media. For instance, the Twitter developer platform offers API solutions for both academic researchers and industrial practitioners. After data collection, there were two categories of data: structured data and unstructured data. Structured data, such as the number of likes, retweets, and comments, are predefined, numeric, unifacted, and non-concurrent and can be accessed and processed directly into a more advanced model (Balducci & Marinova, 2018). In contrast, unstructured data, such as textual content, are characterized as nonnumeric, multifaceted, and concurrent representations (Balducci & Marinova, 2018) and must be converted into a structured format (Dey et al., 2011). Data cleaning must first be conducted to process unstructured textual data, including lower-case letter transformation, punctuation, digit removal, stop word removal, and stemming/lemmatization (Yang & Zhang, 2018). When cleaned data are prepared, analysts can use different natural language processing (NLP) techniques to extract competitive intelligence, including sentiments and topics from the firm-generated content. Topics can be discovered through topic modeling, which requires unsupervised algorithms, such as Latent Dirichlet Allocation (LDA) (Blei et al., 2003), while

sentiment can be extracted using either supervised or unsupervised algorithms.

The key difference between the two categories of algorithms is whether the labeled class exists in the training dataset (Alloghani et al., 2019). Supervised learning attempts to predict and classify predetermined attributes, whereas unsupervised learning is suitable for clustering and association mining (Alloghani et al., 2019). Previous empirical evidence suggests that supervised algorithms outperform unsupervised algorithms in automated text classification tasks (Hartmann et al., 2019). Therefore, in our framework, we suggest using supervised machine-learning approaches to conduct sentiment analysis. However, one disadvantage of supervised algorithms is that they require human coding to create sentiment labels in the training set (Hartmann et al., 2019). Therefore, we recommend using pretrained supervised learning models in major cloud computing services (e.g., Amazon AWS, Google Cloud, and Microsoft Azure) to maximize the working efficiency, especially when the corpus to be analyzed contains a large number of documents. Previous findings suggest that cloud computing services significantly mitigate a series of informational and marketing barriers (Hosseini et al., 2019).

The second phase consists of making use of gained intelligence to predict customer engagement in social media. When all the data are transformed into a structured format, a more advanced analysis can be employed. Analysts can specify predictive models using the structuralized features (i.e., sentiment and topic labels) as well as the original structured features (e.g., published time, published day, and media type) to predict the dimensional facets of customer engagement in social media (i.e., number of likes, shares, and responses).

4. Implementation of the framework: A case study of the leading American fast-food brands

In line with previous social media competitive intelligence studies (He, Shen, et al., 2015), we also used a case study to illustrate how to implement our social media competitive intelligence framework for decision support. The case study was used because it is not only an empirical endeavor (Gerring, 2004) to justify the applicability of our framework, but also fits in the research with exploratory nature (Gerring, 2004). In this case study, we chose the catering industry as the context because it has been one of the most affected sectors during the COVID-19 pandemic (Brewer & Sebby, 2021; Sharma et al., 2020; Yang et al., 2020). Due to the lockdown and epidemic prevention measures, the opening hours of many restaurants are restricted, and people in many countries cannot dine in the restaurant. American brands were chosen because the United States was one of the countries most severely affected by the COVID-19 pandemic based on infection and death rates (Our World in Data, 2021).

In line with the proposed framework, the research process of the case study was divided into two phases. In the first phase, we extracted sentiment and topic labels from the catering brands. In the second phase, we used structuralized features to predict customer engagement in social media, and the performance of the predictive model was evaluated.

4.1. Phase one: extraction of social media competitive intelligence

Methodology. According to the ranking of the 25 most valuable restaurant brands in the world (Brand Finance, 2021), we manually examined and selected the corresponding official brand accounts on Twitter using the following criteria: 1) The brand account should have been verified

on Twitter and 2) the brand should operate its official Twitter account in the United States market. We found that Haidilao and Wetherspoons did not have official accounts in the United States; therefore, they were screened out. We then used Twitter API V2 to collect the tweets generated by the mentioned 23 brands from March 10, 2019 to February 28, 2021; 9733 tweets were collected. The demarcation point before and during the epidemic was March 11, 2020, when the WHO declared the start of the COVID-19 pandemic (WHO, 2020). Additionally, we screened out 666 retweets and 361 non-English tweets, leaving 8721 tweets in the dataset.

For topic modeling, we used the LDA algorithm (Blei et al., 2003) to explore the topics among the textual data. The LDA algorithm is an unsupervised machine learning technique for discovering hidden topics from a large amount of textual data (Jalali & Papatla, 2019; Zhang et al., 2017). For sentiment, we used a cloud-based machine learning service, Amazon Comprehend, to obtain sentiment labels for the tweets in the corpus.

Results. The basic information of the 23 catering brands is summarized in Table 2, including headquartered country, name of the Twitter Account in the United States, number of followers, number of followings, number of being listed, number of tweets (all time), number of tweets (in the period of 2019/03/01 – 2021/02/28), and percentage of tweets (in the period of 2019/03/01 – 2021/02/28).

(Insert Table 2 about here)

Figure 2 shows the volume of the tweets published by the 23 catering brands from March

10, 2019 to February 28, 2021, and the dotted line represents the outbreak of the COVID-19 pandemic. From this figure, we observe that firms' reactions to the pandemic are different in social media. While the volume of some brands (e.g., Dunkin' and Costa) increased after the outbreak, the volume of some brands (e.g., Starbucks and Tim Hortons) did not change notably before and after the pandemic.

(Insert Figure 2 about here)

Regarding the valence of the tweets (see Figure 3), whether before or after the COVID-19 outbreak, tweets with neutral sentiments dominated, followed by those with positive, negative, and mixed sentiments.

(Insert Figure 3 about here)

Following the best practices for conducting the LDA model (Maier et al., 2018), we preprocessed the unstructured textual data, removing uniform resource locators (URLs), digits, and special characters (except “#”, which refers to topic; and “@” which refers to mentions of another person or entity on Twitter). Then, we tokenized the documents in the corpus and converted all the words into the lower case before lemmatizing them. We used lemmatization instead of stemming because lemmas are more interpretable than stems (Maier et al., 2018). Moreover, we removed the stop words (e.g. “a,” “the,” “is,” “are”), because these words usually do not have analytical values in LDA modeling (Yang & Zhang, 2018). We listed the top 30

terms before and during the pandemic in Figure 4. According to the results, the most frequently used words before and during the pandemic were different. Apart from the commonly appeared terms in the normal situation like “order” or “pizza,” during the pandemic, the catering brands were prone to use the terms in line with the marketing strategies used during the pandemic, such as “app,” “delivery,” and “contactless.”

(Insert Figure 4 about here)

When specifying an LDA model, the number of topics, k , must be defined *a priori* (Maier et al., 2018). However, although the k value is crucial to the performance of LDA modeling, finding an appropriate value is challenging (Cao et al., 2009). To determine an adequate number of topics, researchers usually run several candidate models with different k values (Maier et al., 2018). In this research, we used the *FindTopicsNumber* function of the *ldatuning* package to automate this process. We tested 19 LDA models specifying k values ranging from 2 to 20, and evaluated their performances using the Cao Juan metric (Cao et al., 2009), Arun metric (Arun et al., 2010), and Deveaud metric (Deveaud et al., 2014). An LDA model with lower Arun and Cao Juan metrics and higher Deveaud metrics suggest a better solution. The results of the model tuning are shown in Figures 4 and 5. On the one hand, in the LDA models with data from the “Normal” subset (see Figure 5), an explicit elbow appears when the k value is equal to 5. On the other hand, in the LDA models with data from the “Pandemic” (see Figure 6), the explicit elbow can be found when the k value equals 12. These results indicate that 5 and 12 are the optimal k values for the “Normal” and “Pandemic” subsets, respectively.

(Insert Figure 5 about here)

(Insert Figure 6 about here)

After confirming the key values, we used variational expectation maximization (VEM) sampling for LDA modeling. We used VEM sampling instead of Gibbs sampling because previous empirical evidence suggests that VEM performs better in corpuses with a large number of documents (Kherwa & Bansal, 2018). After applying the LDA algorithm for the “Normal” and “Pandemic” subsets, we obtained the beta values for the terms in each topic. The beta value reveals the probability that a term belongs to a topic (Silge & Robinson, 2017). Figures 7 and 8 show the visualizations of beta values of the terms from the “Normal” and “Pandemic” subsets.

(Insert Figure 7 about here)

(Insert Figure 8 about here)

Using the visualizations of the beta values to interpret the results of LDA is not easy (Silge & Robinson, 2017), therefore, we also considered documents with high gamma values (gamma > 0.7) when interpreting the results. The gamma value reveals the probability that a document belongs to a specific topic (Silge & Robinson, 2017). Later, we labeled the topics suggested by the LDA algorithm considering the terms with high beta values and documents with high gamma values. We found that the documents in the “Normal” subset pertain to the following topics: “1-Food and lifestyle,” “2-Promotion,” “3-Food ordering,” “4-Food time,” and “5-Food

delivery.” The documents in the “Pandemic” subset pertain to the following topics: “1-Food time,” “2-Coupons and offers,” “3-Theme day for foods,” “4-Social responsibility,” “5-Food and lifestyle,” “6-Brand specialty,” “7-Warmth conveying,” “8-Calls to purchase,” “9-News sharing,” “10-Sense of taste,” “11-Event promotion,” and “12-Contactless ordering and delivery.” In Table 3, we summarize the labeled topics with descriptions and examples.

(Insert Table 3 about here)

Figures 9 and 10 show the sentiments in each topic before and during the pandemic. The results show that catering brands tend to use a neutral tongue when posting tweets. However, they tend to express positive emotions for three topics during the pandemic, including “Theme day for foods,” “Social responsibility,” and “Warmth conveying” Moreover, they rarely uses negative or mixed tongues in all topics, whether before or during the pandemic.

(Insert Figure 9 about here)

(Insert Figure 10 about here)

4.2. Phase two: prediction of customer engagement in social media

Methodology. In this phase, we used structured textual data along with other originally structured data to predict customer engagement in social media. In Twitter, there are several dimensions of customer engagement, including retweets (rebroadcast on Twitter) and responses (Leek et al., 2019). In this case study, we illustrate the predictive function of the social media

competitive intelligence framework using retweets as the outcome variable. The retweet was selected as the outcome variable because it features the advantage of social media: if the message on social media is rebroadcasted, its influence can reach a large audience at no cost to firms (Jalali & Papatla, 2019). Through users' rebroadcasting behavior, marketing practitioners can reach potential customers who are not actively following the brand account of their firm (Zhang et al., 2017).

One of the challenges faced by firms when conducting social media competitive analytics is determining how their performance stacks against their key competitors' performance (He, Wu, et al., 2015). Therefore, setting a benchmark is important in the social media competitive intelligence framework (He et al., 2015). In this case study, we set the benchmark of the retweet volume to 25 because it was the median value of the sampled brands in the catering industry. This means that if a firm's messages on Twitter are constantly retweeted more than 25 times, the firm gains a competitive advantage over some of its competitors. Therefore, in this case study, we trained the classification models to select the model that most accurately predicted users' retweet behavior.

Based on previous findings, we selected nine independent variables as the predictors of users' retweet behavior, which are Food type (Schultz, 2017), Published time and day of tweet (Cvijikj & Michahelles, 2013; Imran & Han, 2017; Sabate et al., 2014), Published day of tweet (Cvijikj & Michahelles, 2013; Imran & Han, 2017; Sabate et al., 2014; Schultz, 2017), Media type (Annamalai et al., 2021; Chandrasekaran et al., 2019; Sabate et al., 2014; Wang & McCarthy, 2021), Mention (Liu et al., 2021), Hash tag (Araujo et al., 2015), Link (Annamalai et al., 2021; Chandrasekaran et al., 2019; Sabate et al., 2014; Wang & McCarthy, 2021),

Sentiment (Chandrasekaran et al., 2019), and Topic (Jalali & Papatla, 2019; Zhang et al., 2017).

Descriptions and sources of reference are summarized in Table 4.

(Insert Table 4 about here)

In this study, we used six state-of-the-art machine learning algorithms to specify the classification model including the: support vector machine (SVM) with radial basis kernel (Amari & Wu, 1999), CART tree (Breiman et al., 1984), C5.0 tree (an improved version of the original C4.5 algorithm (Quinlan, 2014)), random forest (Breiman, 2001), bagged CART (Breiman, 1996), and gradient boosting (Friedman, 2001). The aforementioned algorithms were selected as candidates for the final classifier because they are the most used machine learning algorithms to conduct the classification task (Kuhn & Johnson, 2013).

We included documents with high gamma values ($\text{gamma} > 0.7$) from topic modeling (Phase 1) in the predictive model. There were 2661 observations in the data of the normal situation and 1117 observations in the data of the pandemic situation. Due to the heterogeneous nature of the data before and during the pandemic, we modeled the classifiers separately using data derived from normal and pandemic situations.

When applying machine learning-based predictive models, there are several challenges. The first challenge is the problem of overfitting. Model overfitting refers to the situation in which the observations are well predicted using the training data, but demonstrate poor performance when using the testing data (Kuhn & Johnson, 2013). Overfitting occurs when the model learns the characteristics of each sample's unique noise instead of the general pattern in

the data (Kuhn & Johnson, 2013). To reduce model overfitting, as suggested in the literature (Humphreys & Wang, 2018), we used k -fold cross-validation. When implementing this method, observations were randomly split into k similarly sized groups. While one group was used as a test set, the others were used to develop the model. The groups were shuffled, and the process was repeated until every group was used as the test group. Moreover, the results were averaged together to provide an estimate of the predictive accuracy. Specifically, we used repeated 10-fold cross-validation, as this method is ideal for datasets with a limited sample size (Kuhn & Johnson, 2013).

Another challenge of applying a machine learning approach is that many algorithms have important parameters that cannot be directly estimated from the data. This type of model parameter is referred to as a tuning parameter because there is no analytical formula available to calculate the value *a priori* (Kuhn & Johnson, 2013).

To overcome these two challenges, we used the resampling and tuning process, which was introduced by Kuhn and Johnson (2013, p. 66). First, we defined a set of candidate values for the tuning parameters (see Appendix I in the online material). Second, we resampled the data using repeated 10-fold cross-validation, fitted the models, and predicted the holdouts. 80% of the data in the normal and pandemic datasets were used for training, leaving 20% of the data for testing. Moreover, we used stratified random sampling within the subgroups to control the proportion of each class in the dependent variable. Third, we aggregated the resampling into a performance profile. Fourth, we determined the final tuning parameters. Fifth, we used the final tuning parameters to refit the models with the entire training set.

Accuracy and Kappa were mainly used to assess the performance of the classification

models, as they are widely used to evaluate machine learning-based classifiers (Sasikala et al., 2017). Moreover, we faced a two-level classification problem: “Retweet volume lower than 25” and “Retweet volume higher than 25.” We added additional metrics, including sensitivity, specificity, positive predicted value (PPV), and negative predicted value (NPV), as they offer additional diagnostic information for the evaluation of model performance (Kuhn & Johnson, 2013). The class “Retweet volume higher than 25” was set as the positive event, as it was the positive outcome that we would like to predict. For the software environment, we used the *caret* package in the RStudio environment (Kuhn, 2008) to train and test the classifiers.

Results. Table 5 shows the descriptive statistics of the variables used in the predictive model, which includes the results for both the normal and pandemic data.

(Insert Table 5 about here)

The performance metrics of the six classifiers are presented in Table 6. Moreover, in Figures 11 and 12, the values of accuracy and Kappa for each classifier are visualized.

(Insert Table 6 about here)

(Insert Figure 11 about here)

(Insert Figure 12 about here)

According to the results, we observed that the SVM could be the best classifier as the

performance metrics indicated that this classifier had acceptable performance in the training phase for both the normal situation data (accuracy=0.702; Kappa=0.390) and pandemic situation data (accuracy=0.702; Kappa=0.357). Additionally, the metric values did not decrease dramatically in the testing data: while the accuracy and Kappa were 0.697 and 0.383 for the normal situation data, the accuracy and Kappa were 0.704 and 0.354 for the pandemic situation data.

However, similar to other top-performing machine learning models, SVM is a black-box algorithm (Bohanec et al., 2017). Therefore, the knowledge that the classifier learns during training is not comprehensible to human beings. Therefore, the results of machine learning-based models are often difficult to interpret, which hinders the generation of managerial insights (Vermeer et al., 2019). Therefore, in line with Vermeer et al. (2019), we considered that managerial considerations should be taken into account when interpreting the results of machine learning models. Therefore, although in our case study, SVM was ideal for prediction, considering the performance and interpretability, we chose the results of the C5.0 classifier for interpretation. In contrast with the SVM, C5.0 is a white box algorithm, which means that the inner mechanism of the model is more interpretable.

The whole trees generated by the C5.0 classifier with the data of normal and pandemic situations were relatively large (see Appendices II and III in the online material). Therefore, in this case study, we only selected a subtree of the C5.0 classifier with pandemic data as an illustration to interpret the results. Figure 13 shows a subtree of the C5.0 classifier with pandemic data, which is a branch of the whole tree. This branch is derived from the branches when food type is Burger/Sandwich, Coffee/Dessert, or Fried chicken, and the topic is about

“Sense of taste.” According to the results, we observed that when firms in the Burger/Sandwich subsector published tweets in the morning with images, the retweet volume was more likely to catch the industry benchmark (Retweet volume ≥ 25). In contrast, when firms published tweets at night, they were more likely to receive fewer rebroadcasts (Retweet volume < 25).

(Insert Figure 13 about here)

When modeling the classifiers, there is a need to quantify the strength of the relationship between predictors and outcomes (e.g. Singh et al., 2017). Therefore, ranking the importance of predictors can be useful for predictive models (Kuhn & Johnson, 2013). Moreover, predictive models have built-in or intrinsic measurements of predictor importance, and C5.0 is one of them. Figure 14 shows the importance of the variables in the classifiers with the data of normal and pandemic situations. According to the results, the posting time, the existence of mention, media type, the existence of hashtags, and the subsector of the catering industry are the most important predictors in the data of normal situations. In the data of the pandemic situation, the topic of tweets, the sentiment of tweets, the days of the week, and the subsector of the catering industry are the most important predictors. It is also observed that the sentiment and the topics of tweets are less important in the normal situation, but their importance increased dramatically during the pandemic.

(Insert Figure 14 about here)

5. Discussion and implications

5.1. Discussion

In this research, we introduced a refined framework for social media competitive intelligence. In this framework, we highlighted the impact of the external environment on the nature of the data. Moreover, we discussed that one of the important values of gained competitive intelligence is to predict customer engagement behaviors in social media. Later, we used a case study to illustrate the application of the proposed social media competitive intelligence framework using 23 catering brands that operated in the United States. Specifically, we illustrated how intelligence from unstructured data on Twitter was extracted and employed to assist marketing decisions. The main empirical results of this research are discussed below.

In phase 1 of the case study, via sentiment analysis, we found that neutral sentiment predominated in the firm-generated content on Twitter, followed by positive, negative, and mixed sentiments. This finding is consistent with the results of previous research, in which four catering services of two retail chains were investigated (He, Shen, et al., 2015). Contrary to intuition, firms prefer to publish content with neutral instead of positive sentiment in their commercial communication on social media. A possible explanation for this might be that firms wish to establish an impartial and objective image in front of social media users.

Through topic modeling, we identified five topics in the normal situation data and twelve in the pandemic situation data. The empirical results indicate that catering brands were taking different strategies before and during the pandemic. Specifically, the results show that some topics exist in both normal and pandemic situations, including “Food and lifestyle” and “Food time.” Moreover, during the pandemic, firms created a new topic related to the “Sense of taste”.

This type of marketing strategy is called the experiential customer engagement marketing initiative, which centers on intrinsically motivating customers by estimating heightened psychological and emotional connections to brands (Harmeling et al., 2017). Meanwhile, the topic “Promotion” in the normal situation is further refined into two topics in the pandemic situation, which are “Coupons and offers,” “Event promotion,” “Calls to purchase,” “Theme day for foods,” “Brand specialty,” and “News sharing.” A possible explanation for this change is that firms respond to the economic effects of the pandemic on the business. In the pandemic, the survival of a business depends on firms’ ability to treat adverse situations as a turning point (Carracedo et al., 2020). The results reveal that firms were refining their marketing strategies to maintain their competitiveness during the pandemic. Additionally, the topics “Food ordering” and “Food delivery” are merged into one topic, “Contactless ordering and delivery.” We considered this shift to be related to customers’ behavioral changes. Due to the lockdown in the pandemic, the dine-in service of catering brands was limited (Yang et al., 2020). Therefore, one of the effects of the pandemic on consumption is that “store comes home” (Sheth, 2020). Thus, during the pandemic, there was no need for catering brands to separate these two topics, because customers were ordering foods from their homes, which tied up ordering and delivery. Also, the topic “Social responsibility” was found in the pandemic situation data, which revealed that firms paid more attention to social responsibility during the pandemic. The pandemic has started a new era in the relationship between corporate social responsibility and marketing (He & Harris, 2020). Researchers suggest that the pandemic offers great opportunities for firms to actively engage in various social responsibility initiatives during the crisis (He & Harris, 2020) and our results indicate that firms are in action to this proposal.

In phase 2 of the case study, we used the gained competitive intelligence from unstructured social media data, including sentiments and topics, along with other structured data to predict customer engagement behavior in social media. We tried six machine learning-based algorithms and found that the SVM with radial basis kernel performed best among all the tested classifiers. Therefore, when firms' goal is to maximize the prediction accuracy, the SVM is suggested to be used in the social media competitive intelligence framework. However, because SVM is a black box algorithm, managers find it difficult to interpret the results. Thus, in the case study, we offered an example to illustrate how to check the internal mechanism of the classifier using a white box algorithm, C5.0. According to the results, the importance of sentiment and topics increased after the outbreak of the pandemic. When firms' goal is to take both predictivity and interpretability into account, we recommended the C5.0 for use in the social media competitive intelligence framework. According to the results of the C5.0, managers should adjust their social media marketing strategies during the pandemic, because the topics and sentiment of tweets are becoming more important than ever. Moreover, marketing practitioners are advised to examine the results of the decision tree. In many cases, the decision tree can become very large, which prevents managers from interpreting it as a whole. However, insightful intelligence can always be found in some branches of the tree. For instance, in the case study, we found that for brands of Burger/Sandwich, Coffee/Dessert, and Fried chicken, one of the actionable strategies to enhance the number of retweets was to post messages related to the topic "Sense of taste" with a strong sentiment in the morning, along with a video. A possible explanation for this result may be that the morning is a critical time for managers to increase the number of retweets (Jalali & Papatla, 2019). Social media posts with strong sentiments, descriptions of

taste and smell, and rich visual and auditory displays may activate customers' cognitive processes. Cognitive processes are associated with customer engagement in social media (Halaszovich & Nel, 2017). This is especially important during the pandemic, when individuals are forced to become teleworkers and experience a routine that repeats day after day.

5.2. Implications

On the theoretical side, we fixed the shortcomings of existing social media competitive intelligence frameworks. Although competitive intelligence generates important business value for firms (Bose, 2008), there is a gap between gained intelligence and decision-making. In this research, we incorporated the influence of the external environment and prediction phase in the social media competitive intelligence framework. This improvement contributes to the social media competitive intelligence literature by expanding the scope of framework use from merely intelligence extraction to customer engagement prediction.

On the practical side, we illustrated the implementation of the proposed social media competitive intelligence framework using a case study. The empirical results of the case study reveal the specific sentiment and topic patterns of the main players in the American catering industry. These results are beneficial for marketing practitioners to analyze evolutionary trends in the catering industry before and during the pandemic. Moreover, although in the case study, we used the catering sector as the context and the retweet as the outcome variable, the proposed framework is expected to be applied in a broader context. For example, marketing practitioners in the retail industry may also apply our framework to enhance the different dimensional facets of customer engagement in social media, such as like and response.

6. Limitations and future research

This research is not without limitations.

First, we used a case study to illustrate the use of the proposed social media comparative intelligence framework. Case studies are known to be more helpful in forming descriptive inferences (Gerring, 2004). However, it is still valuable to generate causal inferences through the machine learning approach (Schölkopf, 2019). Therefore, researchers could closely monitor the latest developments in the machine learning field, such as stable learning (Cui et al., 2020), and incorporate the technique into the social media competitive intelligence framework when the time is ripe.

Second, from the perspective of pure modeling and decision-making, social media competitive intelligence requires efficient data-driven and dynamic decision marking (Zeng et al., 2010). We used the historical tweets published by firms from March 1, 2019 to February 28, 2021 to illustrate the implementation of our decision support framework. When social media competitive intelligence research matures, researchers should develop a real-time computational framework instead of a framework based on historical data (Zeng et al., 2010). Therefore, we highly recommend that future researchers monitor the latest developments in social media APIs (e.g., Twitter API V2) and cloud computing services (e.g., Amazon AWS, Microsoft Azure, and Google Cloud). A real-time decision support framework for social media intelligence is especially needed for fast-changing markets.

Third, in our case study, the empirical results demonstrate that the SVM algorithm is the best classifier. Over the last decade, the SVM algorithm has demonstrated superior performance

to many other classification techniques in a variety of application areas (Barakat & Bradley, 2010). However, the black box nature of this category of techniques is one of the main obstacles impeding their practical application (Barakat & Bradley, 2010). Therefore, due to the interpretability issue, we suggested that readers employ a classifier, the C5.0, that takes both predictivity and interpretability into account. Nevertheless, one of the most cutting-edge research fields in machine learning is rule extraction, which intends to convert an opaque model such as SVM into a transparent model (e.g., Hayashi & Oishi, 2018). Therefore, we suggest that researchers monitor the latest development of rule extraction and incorporate this technique into the social media competitive intelligence framework when the technique is more mature.

Fourth, in our case study, nine predictors were used to train and test the classifiers. However, including additional variables in the classifiers may enhance the model performance. Researchers have found that users' behavior in social media is heterogeneous, as they have different cultural value orientations and demographic characteristics. (Ju et al., 2021). Therefore, researchers are encouraged to incorporate not only firm-generated content but also user-generated content in their classifiers.

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Figure 1. Decision support framework of social media competitive intelligence.

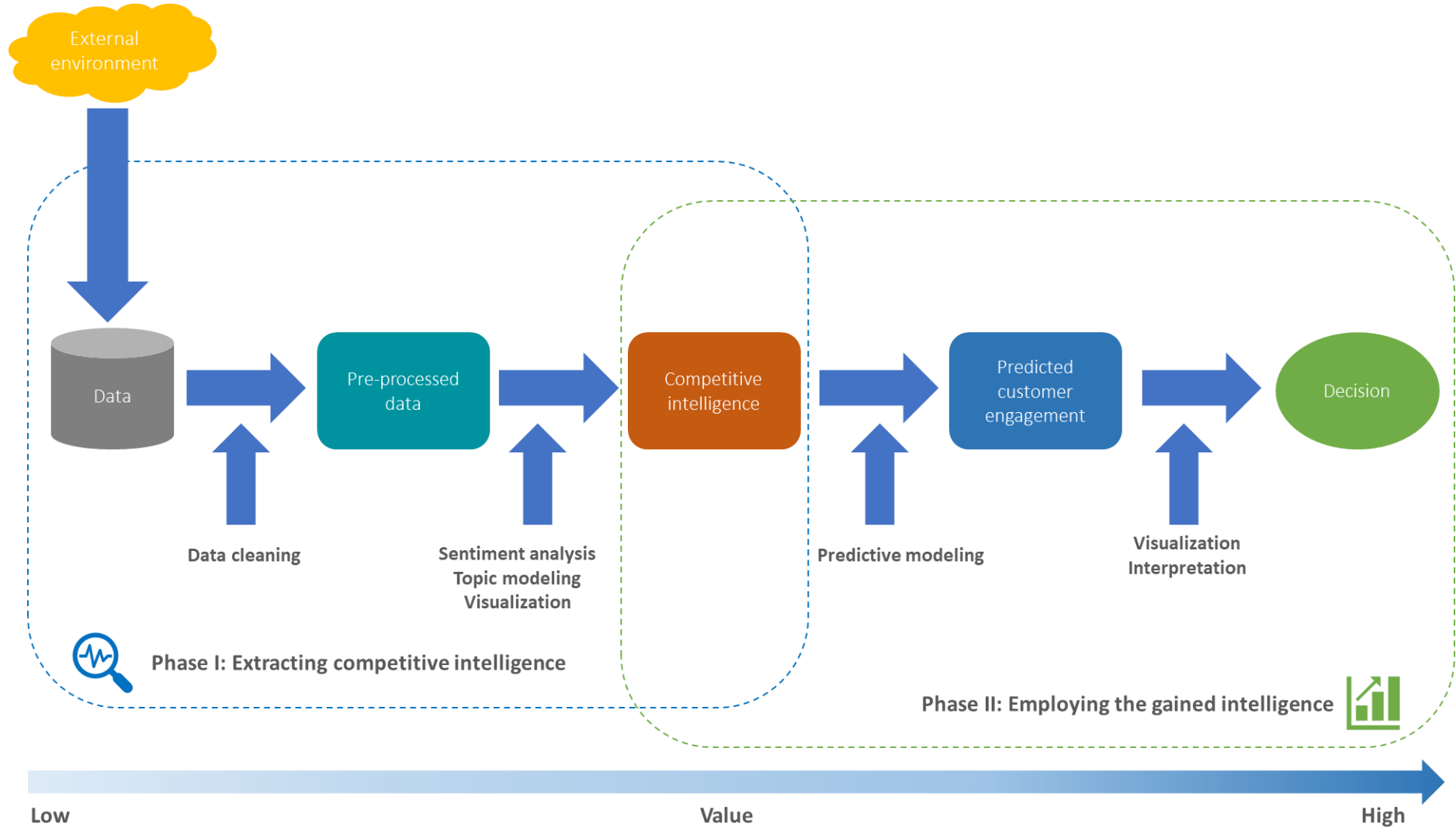


Figure 2. Volume of tweets published by the catering brands from 2019/03/01 to 2021/02/28.

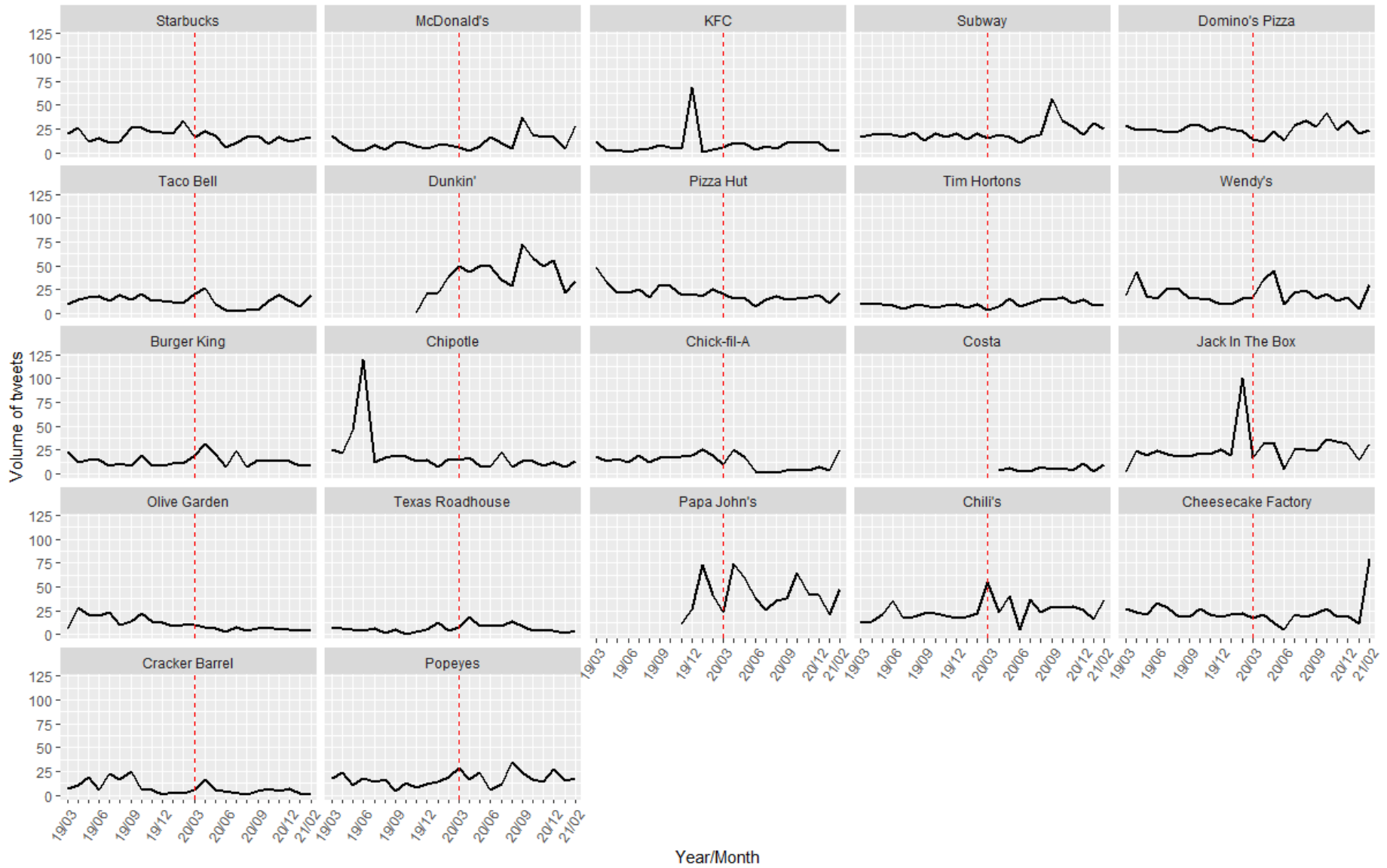


Figure 3. Valence of tweets published by the catering brands from 2019/03/01 to 2021/02/28.

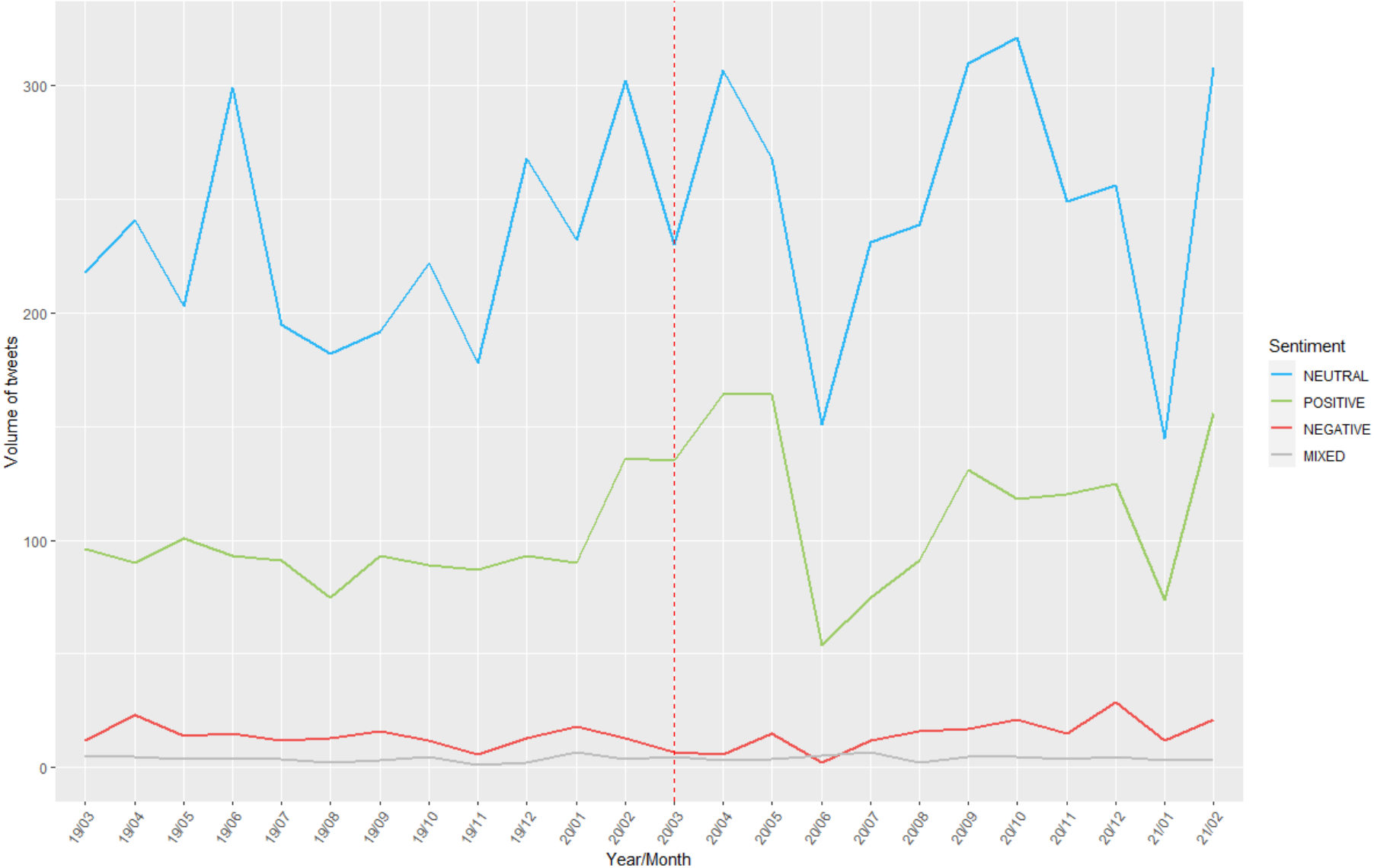


Figure 4. Top terms before and during the pandemic.

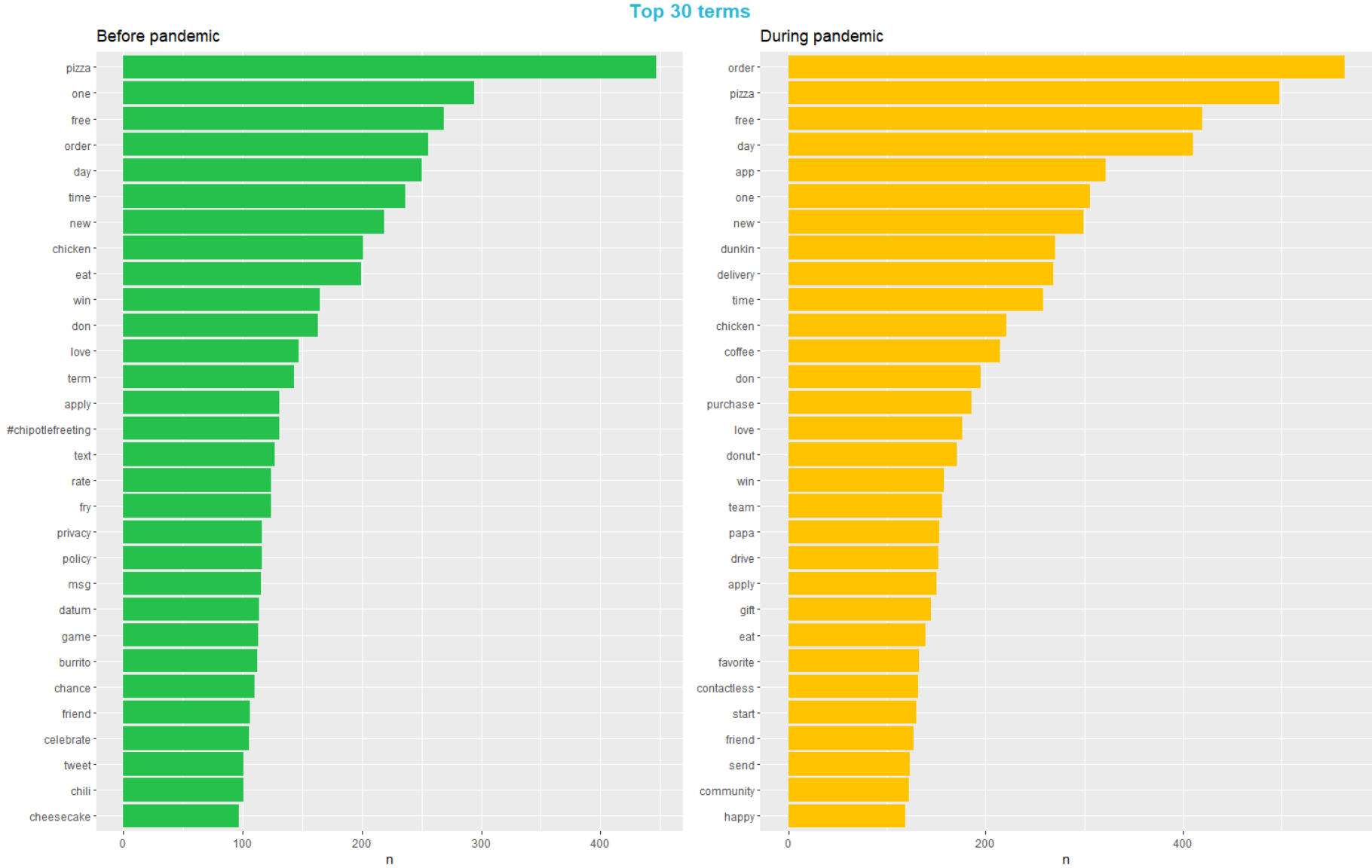


Figure 5. LDA model tuning with data from "Normal" subset.

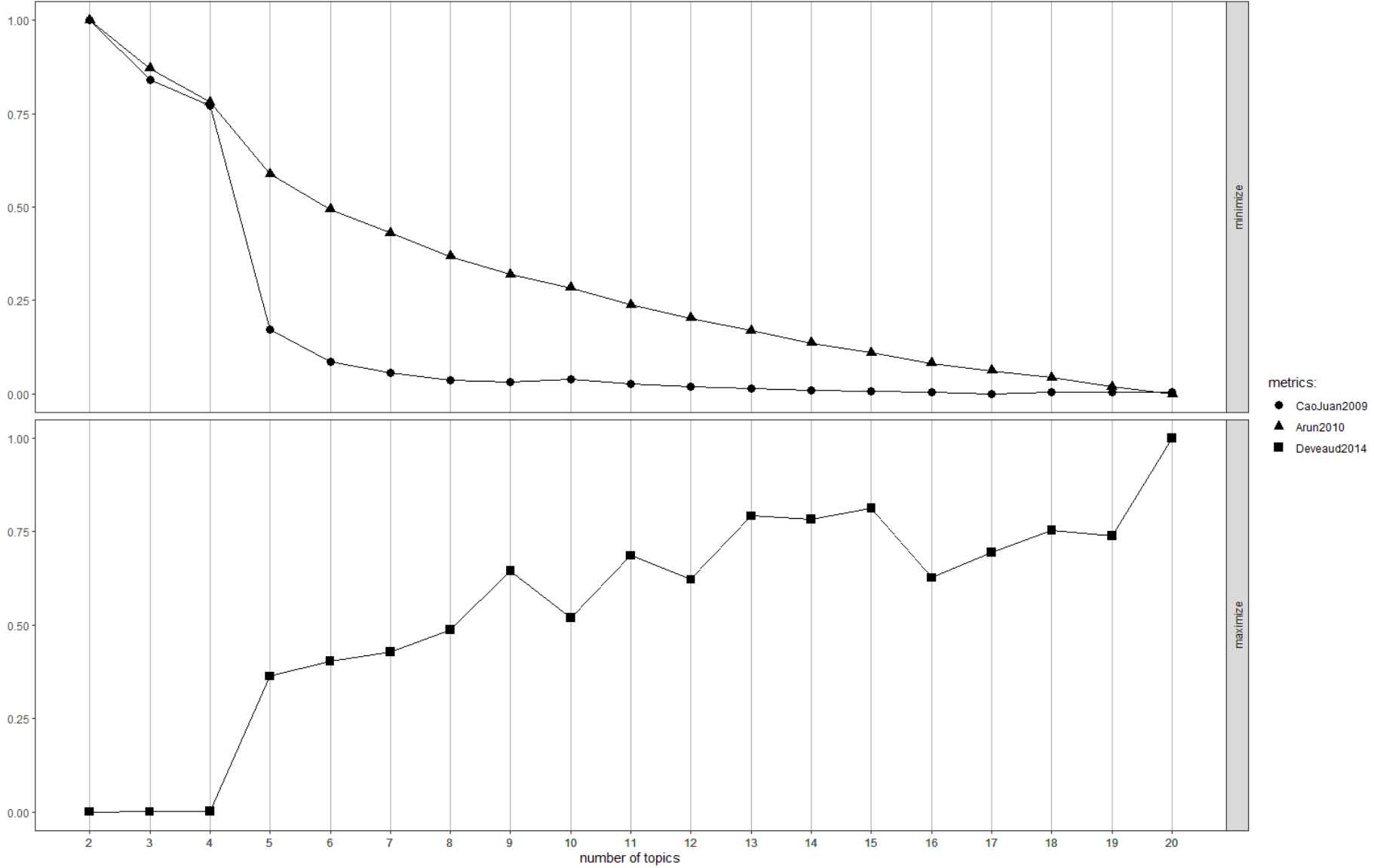


Figure 6. LDA model tuning with data from “Pandemic” subset.

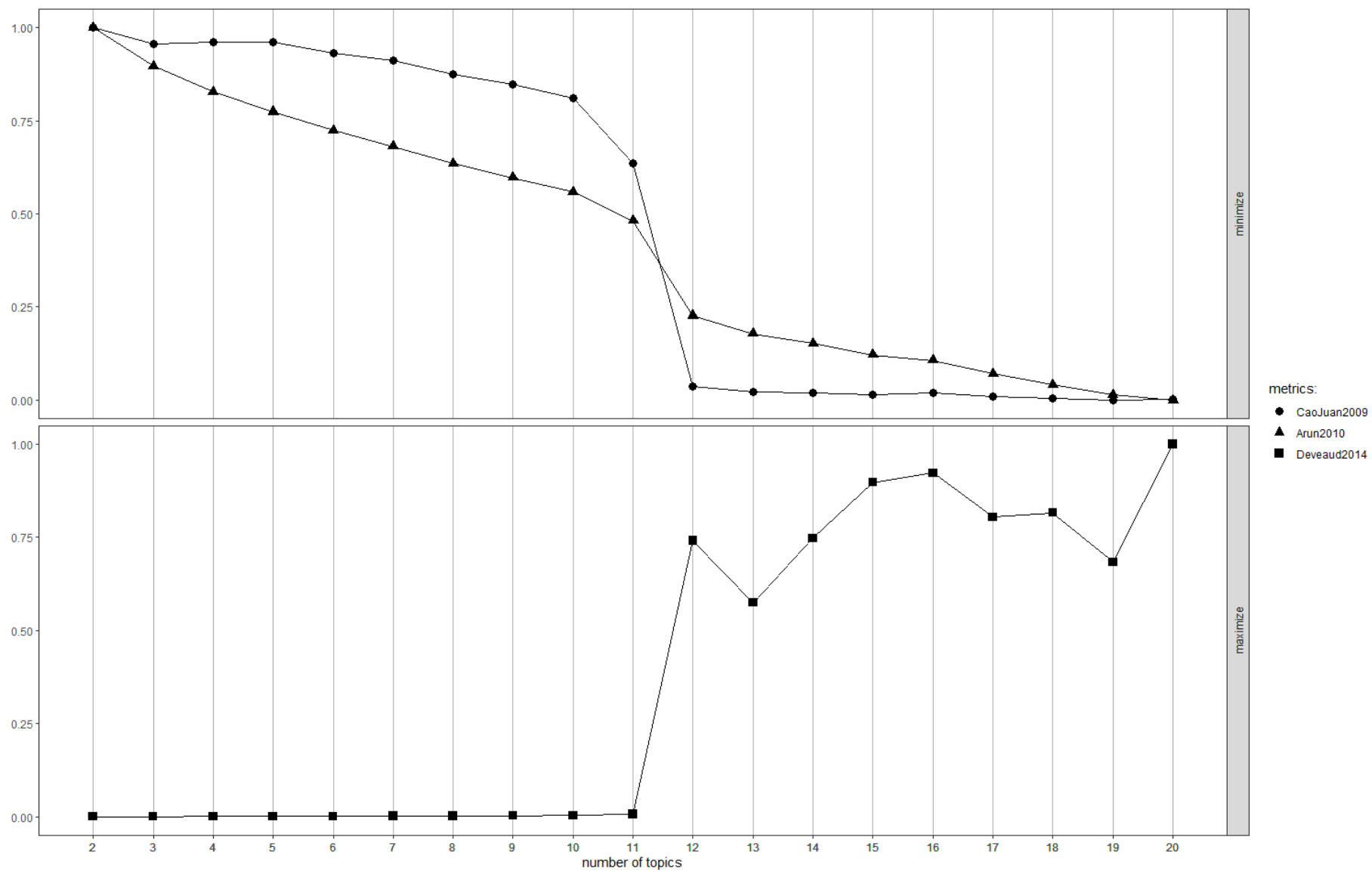


Figure 7. Visualization of the beta values of the terms from the “Normal” subset.

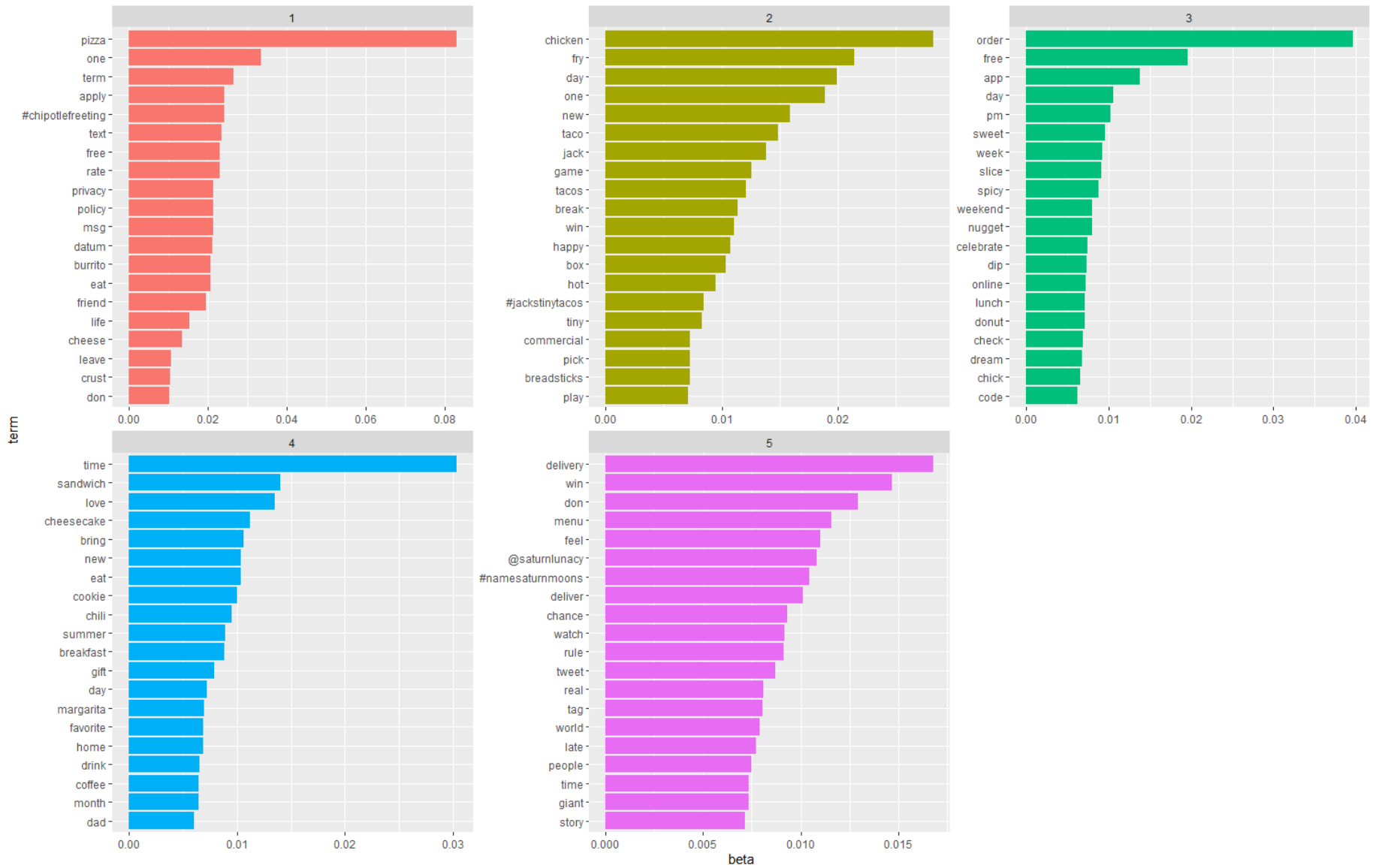


Figure 8. Visualization of the beta values of the terms from the “Pandemic” subset.

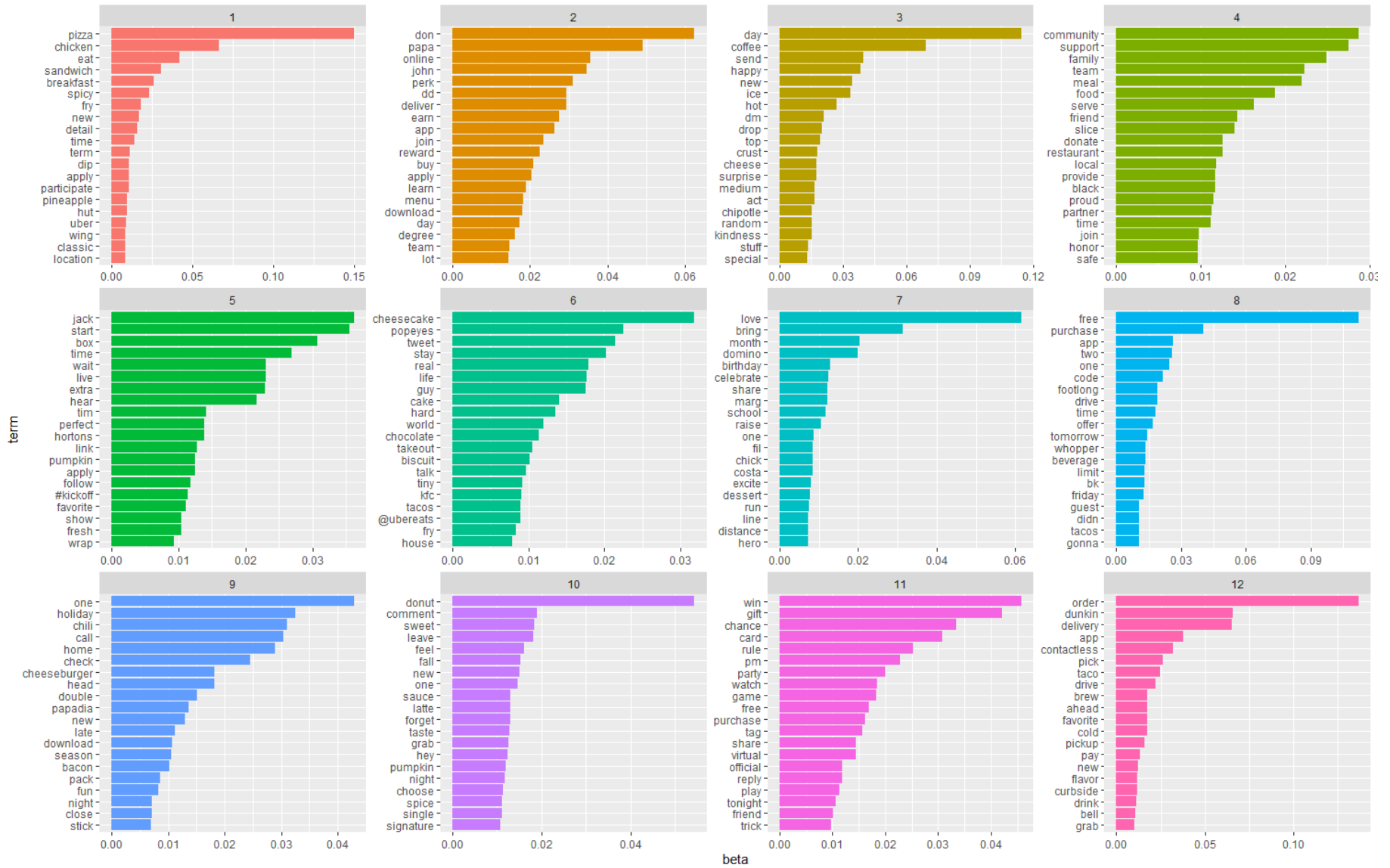


Figure 9. Visualization of the topics and sentiments during the normal situation.

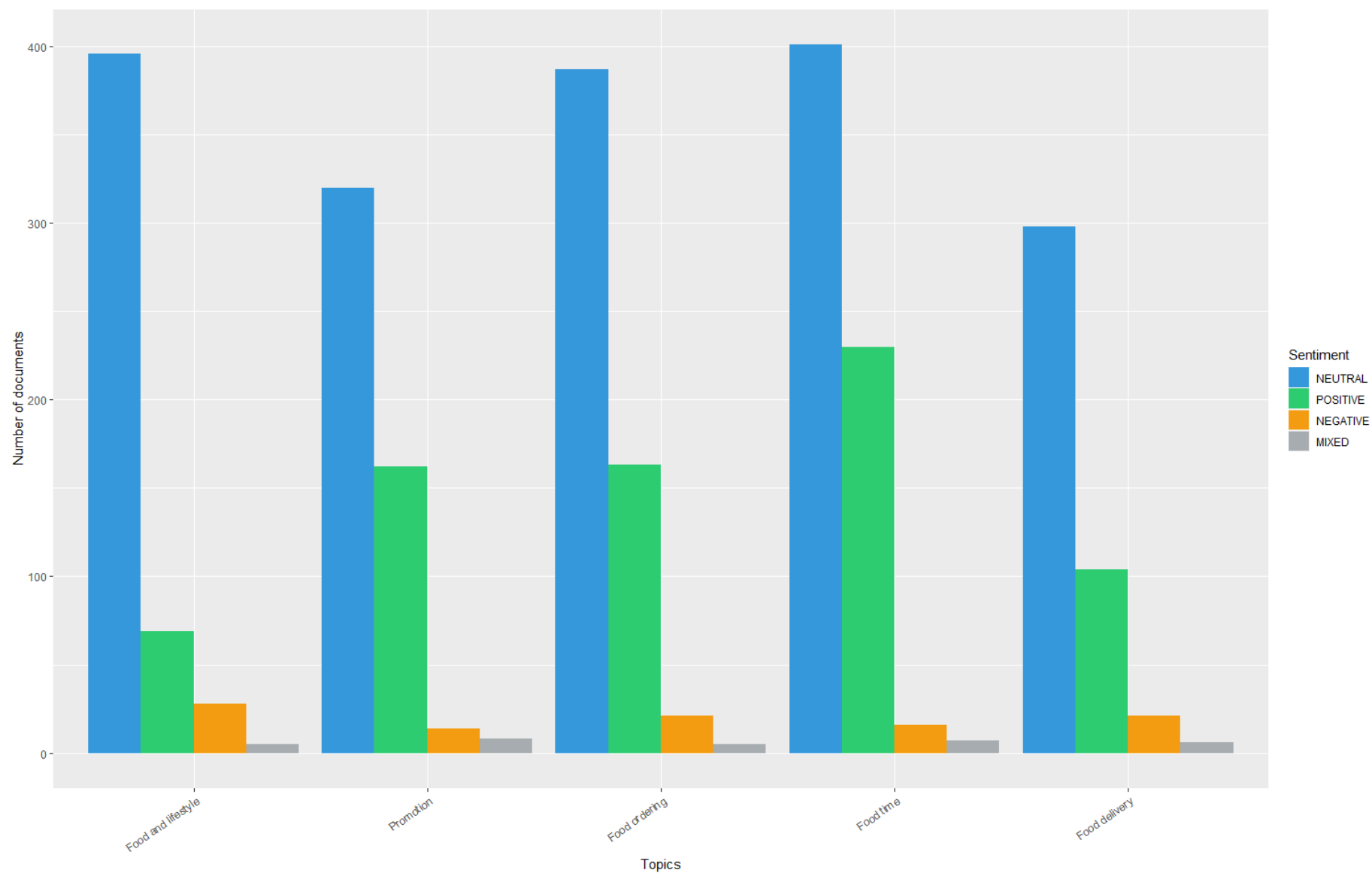


Figure 10. Visualization of the topics and sentiments during the pandemic.

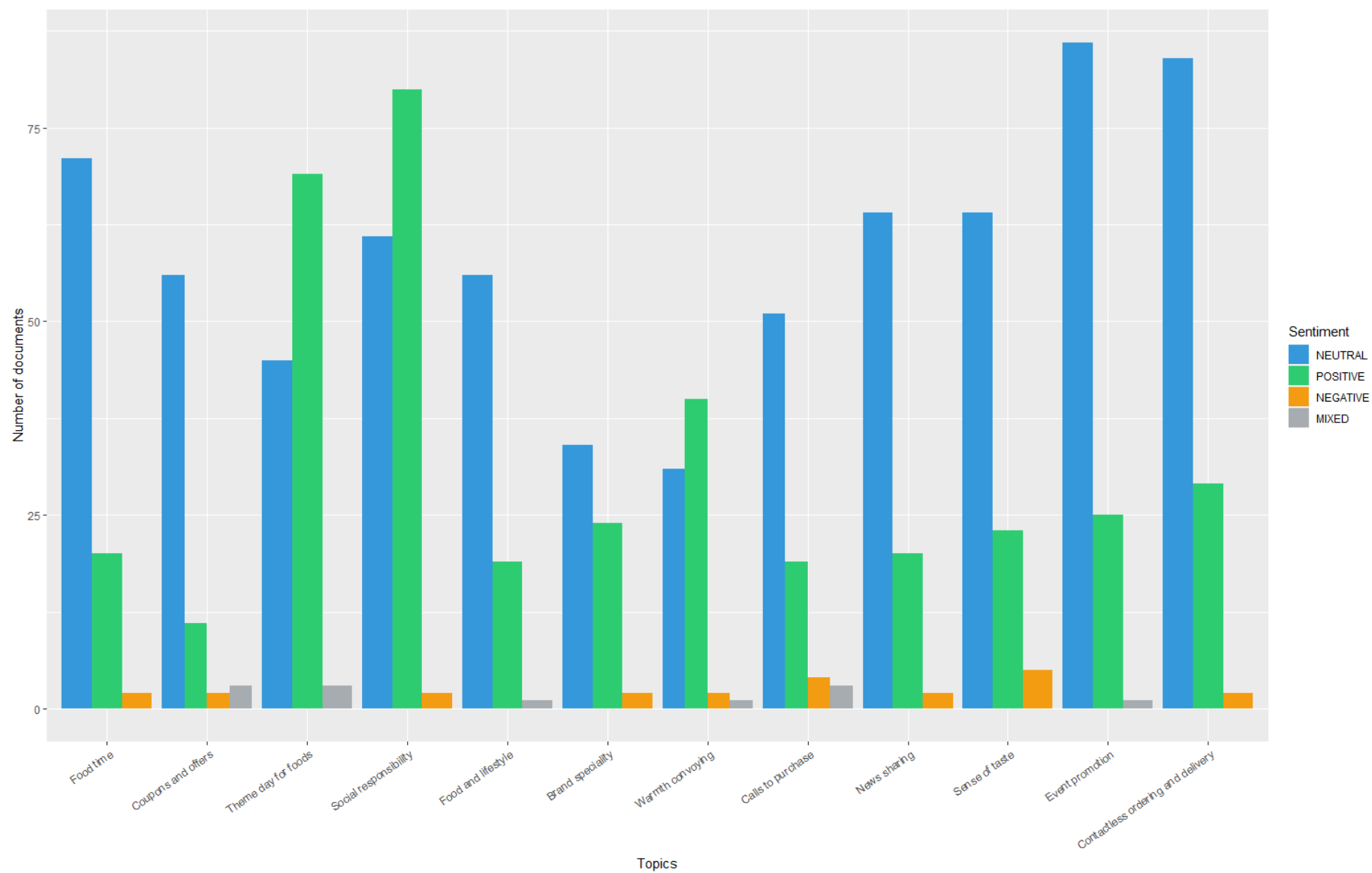


Figure 11. Visualization of the accuracy values for the classifiers.

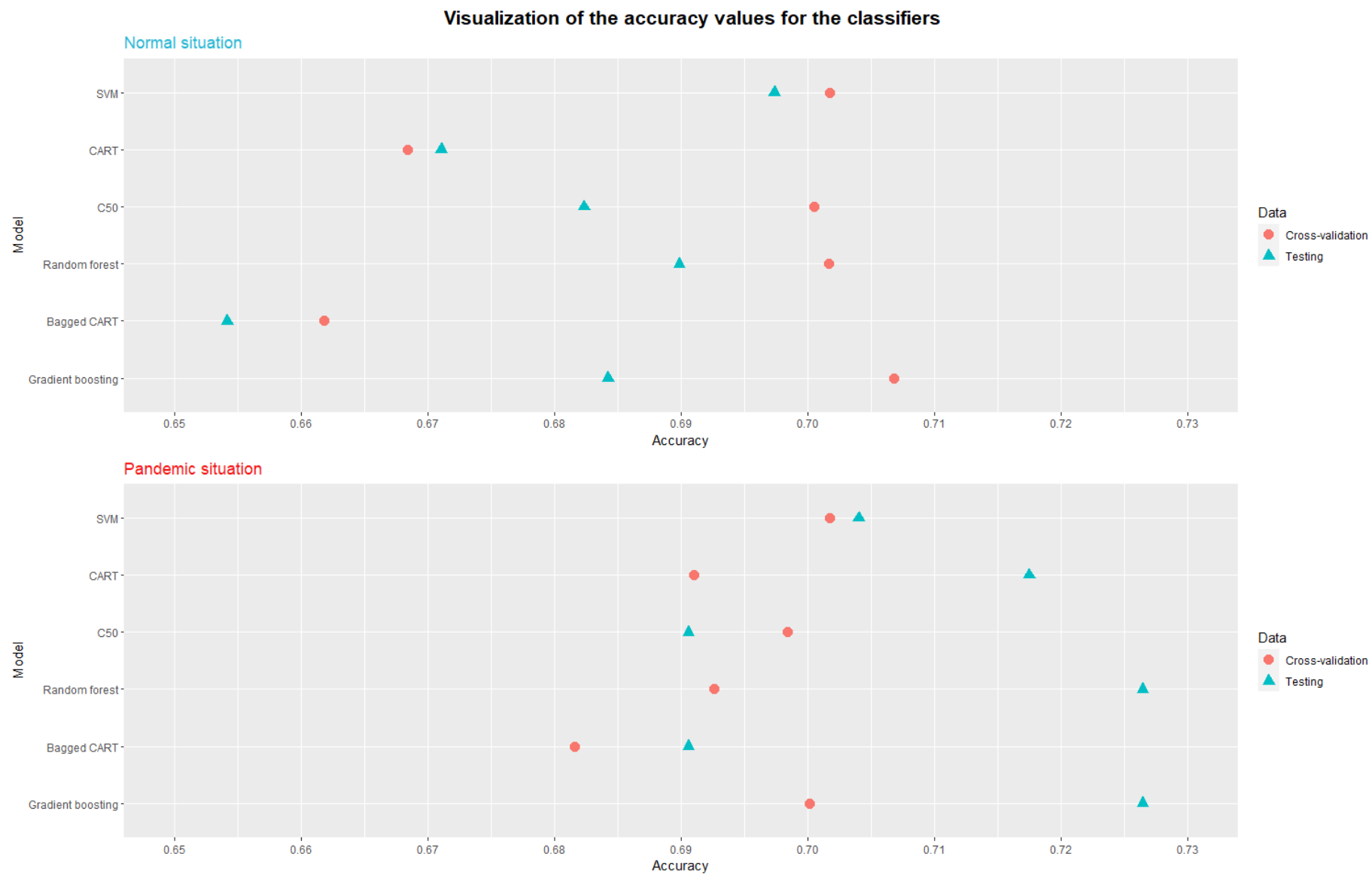


Figure 12. Visualization of the Kappa values for the classifiers.

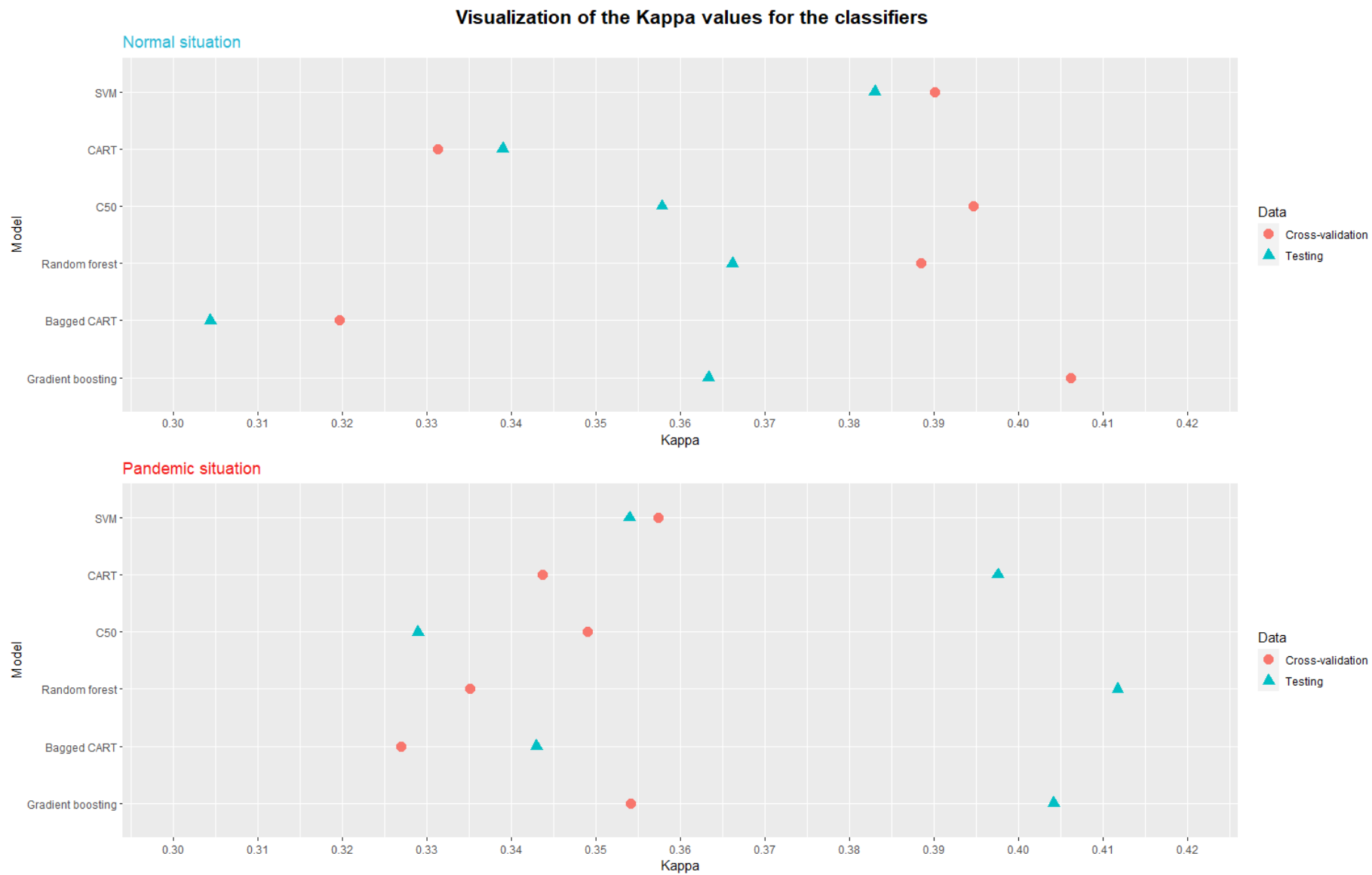


Figure 13. A subtree in the C50 classifier with the pandemic data.

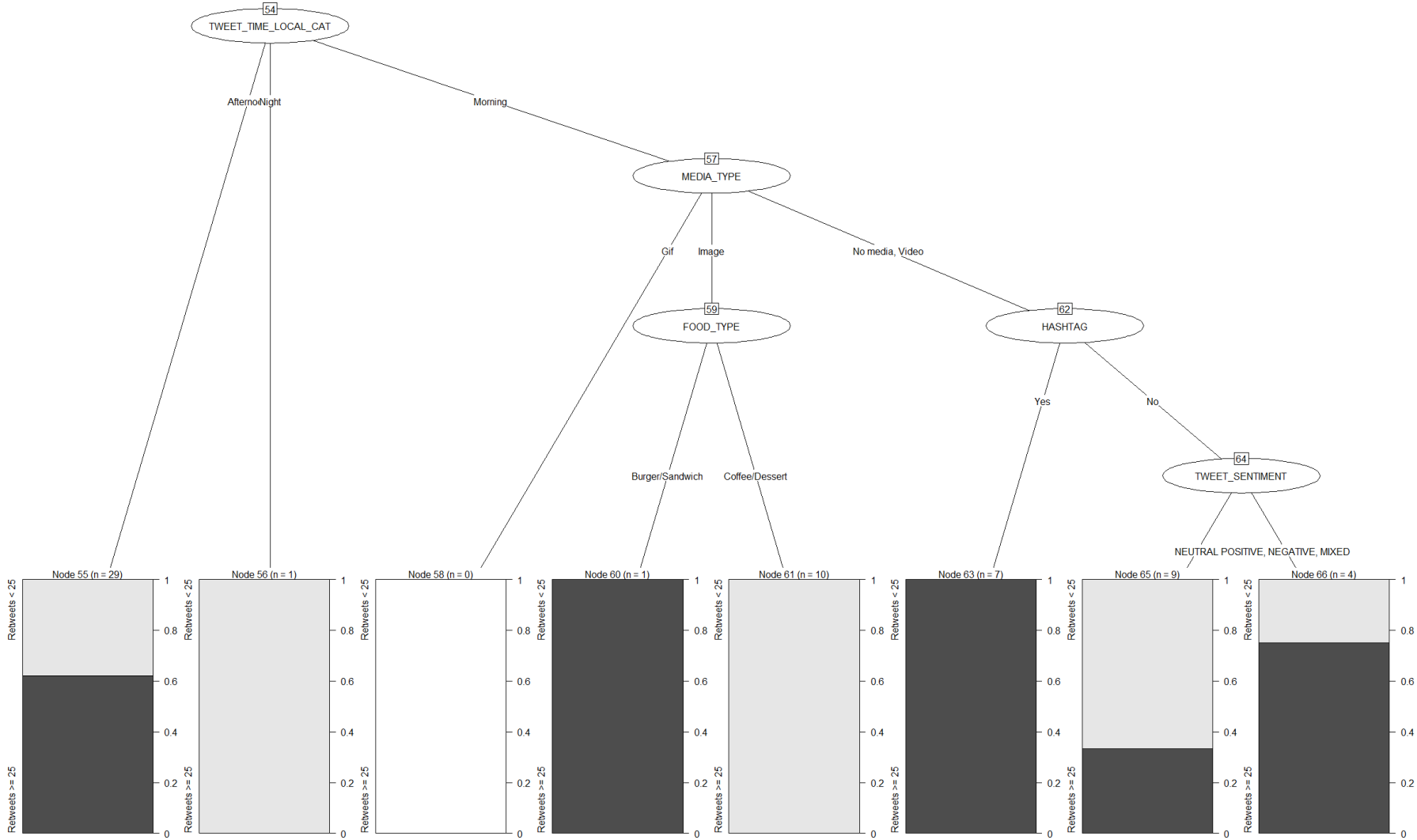


Figure 14. Visualization of the importance values for the C5.0 classifier.

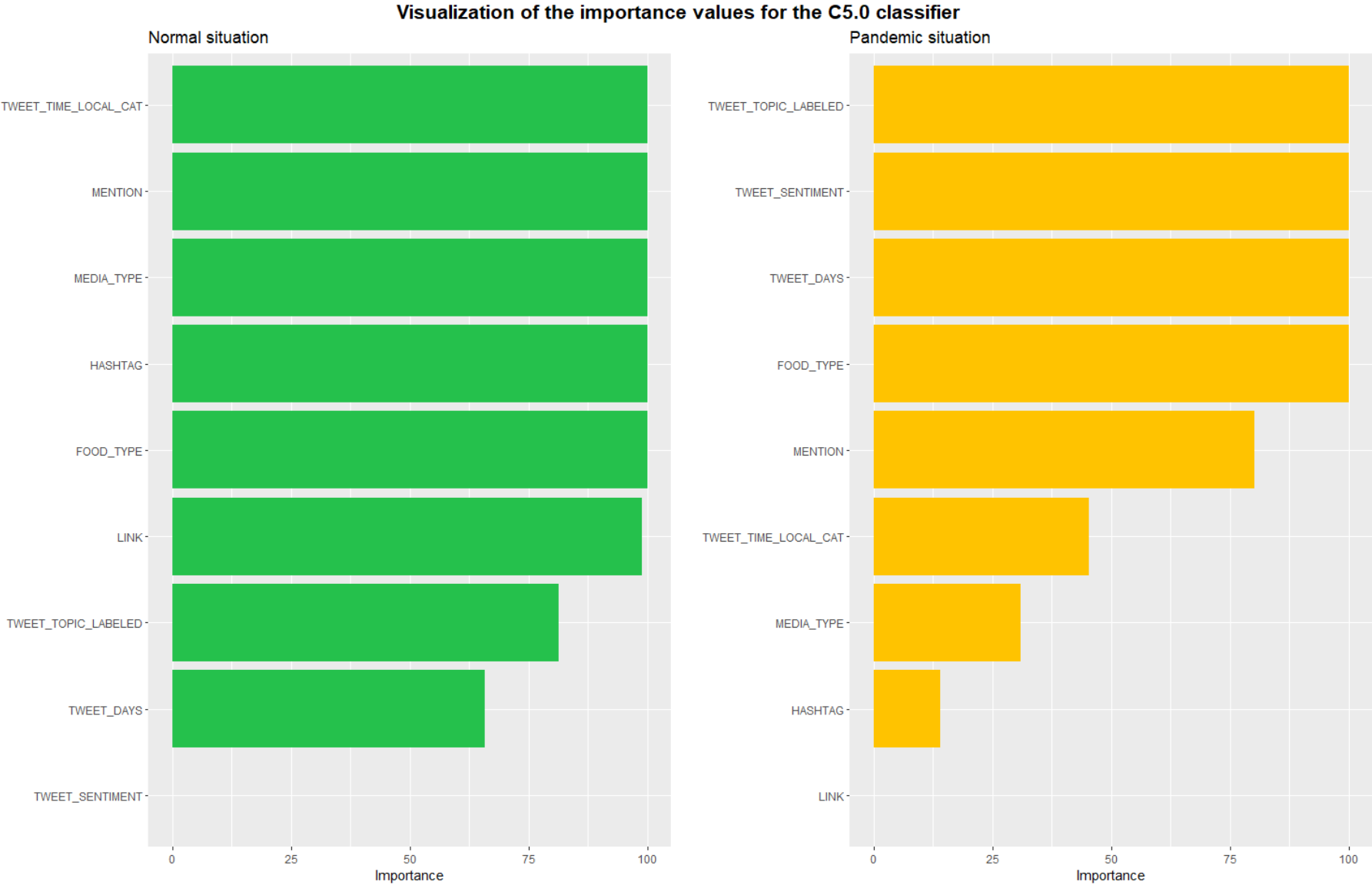


Table 1. Social media competitive intelligence frameworks.

Authors	Objective	Industry	Method		Contribution
			Data collection	Data analysis	
He et al. (2013)	To explore how to perform a social media competitive intelligence analysis and transform data into knowledge for decision makers.	Pizza	User-generated content on Facebook and Twitter from the three largest pizza chains brands was collected.	Case study. Themes analysis.	By comparing customer engagement patterns of different brands in Facebook and Twitter, the study highlights the value of social media data for decision making at the industry level.
He et al. (2015)	To propose a framework for social media competitive intelligence to enhance business value.	Retailing	User-generated content on Twitter from two largest retail chains brands was collected using Twitter API.	Case study. Sentiment analysis.	The study proposes a framework of social media competitive intelligence to illustrate how firms can generate tangible and intangible business value by leveraging social media analytics.
He et al. (2015)	To propose a social media competitive analytics framework with sentiment benchmarks for gaining industry-specific marketing intelligence.	Retailing	User-generated content on Facebook, Twitter, forums, blogs, and other platforms from five retail brands was collected using APIs, RSS, HTML parsing, and manual copying.	Sentiment analysis and themes analysis.	The study develops a novel social media competitive analytics framework with sentiment benchmarks to shed light on how to enhance marketing intelligence and generate business insight reports through various social media competitive analysis.
He et al. (2016)	To develop a framework to explore how social media competitive analytics is applicable for understanding customer experiences.	Retailing	User-generated content on Facebook from the three largest drugstore chains in the United States was collected using APIs, RSS, HTML parsing, and manual copying.	Case study. Concept maps and sentiment analysis.	By comparing the social media use by three drugstore chains and their customer engagement trends, the study provides recommendations to help firms develop social media competitive strategies.
He et al. (2017)	To propose a framework to illustrate how business decision-making can be derived from big social media data.	Retailing	User-generated content on Twitter from five large companies in the retail industry was collected using API.	Case study. Sentiment analysis, concept map, and theme analysis	The study provides practical guidance for valuable knowledge and business intelligence extraction from big social media data.

Ibrahim and Wang (2019)	To explore how companies can learn from customer tweets to improve their online retail service.	Retailing	User-generated content on Twitter from five leading UK online retailers was collected.	Topic modelling, social network analysis, and sentiment analysis.	The study provides a novel framework to transform social media data into useful knowledge and improve online retailing service.
Jimenez-Marquez et al. (2019)	To propose a two-stage framework for analyzing social media content.	Tourism	User-generated content on Yelp from tourism brands was collected using a web crawler.	Case study. Sentiment analysis and machine learning classifier.	The study contributes to tourism and big data literature by developing a novel framework for extracting knowledge from social networks data and testing its capacity.
Arora et al. (2020)	To illustrate how business competitive analysis can be used to detect promoted posts on social media.	Multiple industries	Data comprises of both brand posts and customers' reactions was collected from Facebook using graph API.	Logistic regression, random forests, and extreme gradient boosting.	The study illustrates how social media data can be transformed into knowledge through models.
Yost et al. (2021)	To understand the most important features of active social media engagement and the impact of customer engagement rate on sales of the new product.	Hospitality	Social media posts on Facebook, Twitter, and Instagram from hospitality brand were collected.	Themes analysis, sentiment analysis, and regression model.	By illustrating the customer engagement rate of the brands, the study provides empirical evidence that highly engaged social media posts drive firm performance through increased sales.
Zhan et al. (2021)	To develop a social media analytic framework for improving operations and service management.	Retailing	User-generated content on Twitter from the three largest retail pharmacy organizations in the UK was collected using API.	Case study. Topic modelling, sentiment analysis, and concept maps.	The study provides insights into the use of social media data for developing social media strategies as well as improving operations and service quality.
Our study	To describe how social media competitive intelligence can be used for customer engagement prediction and decision-making.	Catering	Content generated by the leading catering brands in the United States in Twitter was collected using Twitter API.	Case study. Cloud computing-based sentiment analysis, topic modeling, regression tree	The study highlights the impact of external environment on the nature of data and the importance of competitive intelligence in customer engagement prediction and decision support.

Table 2. Basic information of the leading 25 catering brands (Data collected on September 10, 2021).

Ranking	Brand	Headquartered country	Twitter Account in United States	Number of followers	Number of following	Number of being listed	Number of tweet (All time)	Number of tweet (2019/03/01 - 2021/02/28)	Percentage of tweets (2019/03/01 - 2021/02/28)
1	Starbucks	United States	@Starbucks	10923729	91123	25762	249812	418	4.79%
2	McDonald's	United States	@McDonalds	4296808	13543	8946	758323	250	2.87%
3	KFC	United States	@kfc	1538619	11	3595	48131	199	2.28%
4	Subway	United States	@SUBWAY	2293289	30022	5236	107980	506	5.80%
5	Domino's Pizza	United States	@dominos	1375448	536	3757	447651	593	6.80%
6	Taco Bell	United States	@tacobell	1962103	74	4815	795579	314	3.60%
7	Dunkin'	United States	@dunkindonuts	1230053	52786	5546	104070	627	7.19%
8	Pizza Hut	United States	@pizzahut	1637011	77652	4789	492046	497	5.70%
10	Tim Hortons	Canada	@TimHortonsUS	27852	2397	151	8479	218	2.50%
11	Wendy's	United States	@Wendys	3809174	443	5016	205704	479	5.49%
12	Burger King	United States	@BurgerKing	1953213	3827	3624	45989	342	3.92%
13	Chipotle	United States	@ChipotleTweets	1056254	13	3667	929069	480	5.50%
14	Chick-fil-A	United States	@ChickfilA	1132887	7270	3967	200219	314	3.60%
15	Costa	United Kingdom	@costacoffeeus	328	33	11	93	61	0.70%
16	Jack In The Box	United States	@JackBox	118535	10129	1284	40440	625	7.17%
17	Olive Garden	United States	@olivegarden	414806	18085	1225	181071	265	3.04%
18	Texas Roadhouse	United States	@texasroadhouse	105512	28984	436	18588	148	1.70%
19	Papa John's	United States	@PapaJohns	643840	5404	2631	78090	662	7.59%
20	Chili's	United States	@Chilis	402150	25593	1923	414993	591	6.78%
22	Jollibee	Philippines	@JollibeeUSA	1017	0	17	116	0	0.00%
23	Cheesecake Factory	United States	@Cheesecake	354222	13397	1918	38544	550	6.31%
24	Cracker Barrel	United States	@CrackerBarrel	116682	309	515	12366	174	2.00%
25	Popeyes	United States	@Popeyes	245698	5325	1251	62907	408	4.68%

Table 3. Labeled topics with descriptions and examples.

Situation	Topic	Label	Description	Examples
Normal situation	1	Food and lifestyle	Connecting foods with peoples' lifestyle	Find someone you'll share pizza with for the rest of your life.
				You spend 1/3 of your life asleep. The other two thirds is spent thinking about pizza.
	2	Promotion	Ordinary promotions in social media	Life is short. Eat dessert first. 🍩🍷 https://x.xx/xxxxxxxxxxxxx
				Was that a catch??? Either way, you can win incredible prizes during the next commercial break! #JacksTinyTacos
				Blue...43...win free stuff! Tweet #JacksTinyTacos and #Giveaway before this commercial break ends for a chance at Prize Pack 10! https://t.co/xy2wIMFAtQ
3	Food ordering	Calling customers to order foods and introducing channels of ordering	Buy a regular freeze for \$1, get a Doritos Locos Tacos for \$1. Now that’s what we call #HappierHour.	
			Ordering this in... 10 9 8 7 6 5 4 3 2 Done. https://t.co/6kjUYJS4FH	
			Should you order 🍕 pizza for #NationalPineappleDay? yes yes yes yes yes yes yes...	
4	Food time	Recalling customers' memory of approaching food time.	Cyber Monday is here DD Perks Members! So is your last chance to get 3X points on any food or beverage when you order using the Dunkin' App. Exclusions apply. https://t.co/nPaDb1SFAG	
			not sure who needed to hear this today, but it's ok not to be happy all the time. all that matters is that you #FeelYourWay. https://t.co/vPmy1sT0cC https://t.co/XmF0GvMjCg	
5	Food delivery	Introducing the delivery service	It's high time for a brownie 😊. https://t.co/b6rnR7PdT6	
			Longer days mean more time for coffee. 🗺️☕	
Pandemic situation	1	Food time	Recalling customers' memory of approaching food time.	Sometimes the bells mean surrender, other times it means free delivery has arrived. \$10 minimum. Rules: https://t.co/HxyHjC8mxc
				Spicy Nugg delivery knows no bounds @dmainy_13 https://t.co/yfILuE6FOh
	2	Coupons and offers	Giving codes of coupons and offering discount information	Don't leave work - just get your Chili's delivered. You're welcome. #WednesdayWisdom
				If I had a pizza for every time I talked about pizza I'd have a lootttttttttttttttttttttttttt of pizza.
				There's 🍕no 🍕such 🍕thing 🍕as 🍕pizza 🍕time 🍕if 🍕pizza 🍕time 🍕is 🍕all 🍕the 🍕time 🍕
				Apps stand for appetizing right? Time to pizza-fy your phone for #NationalPizzaMonth. https://t.co/Wm80fxoN26
				Let's give a hearty round of applause for your favorite footlongs. \$5 Footlongs when you buy 2 only in app/online. https://t.co/Vkbzoe6Vxj
				Break bread for a lot less dough. Get \$5 footlongs when you buy 2 in the app or online. https://t.co/m8XuKo9he5

			use code BOGO50 in the app or online for buy 1 get 1 50% off Footlongs. tag who you go splitsies with.
3	Theme day for foods	Promoting related products on the theme day	<p>☕ Wake up, it's National Dunkin' Day! ☕ Give your brain a liquid hug and celebrate with a FREE medium hot or iced coffee with any purchase today, 9/29. ❤️ Exclusions & additional charges may apply. https://t.co/zMLm62jTRI</p> <p>Your pup would appreciate a Big Mouth Bite to celebrate #NationalDogDay 🐶 🍔 🍕 https://t.co/loygDHX0mR</p> <p>We all love coffee in our own special way! Let us know how you enjoy a cup while celebrating #NationalCoffeeDay today. ☕❤️ What time of day do you need your coffee most?</p>
4	Social responsibility	Introducing the efforts in social responsibility	<p>KFC is donating 621,240 pounds of food to food banks across the US through its Harvest Program to combat critical shortages created by COVID-19. With this donation, KFC will have provided 1.2 million pounds of food this year. Visit https://t.co/yJZvcSXDWV to learn more. https://t.co/4lGhzSUXo1</p> <p>We are nothing without Black lives.</p> <p>There's no room for injustice. We commit to strengthening every facet of our culture and policies to foster an environment where equality for Black people is a priority. We'll use our platform to support this movement. #BlackLivesMatter</p> <p>We remain committed to investing back in the communities we serve by supporting organizations dedicated to social justice, youth, and education in the Black community.</p>
5	Food and lifestyle	Connecting foods with peoples' lifestyle	<p>You have food at home but it's not pizza hint hint hint hint hint hint hint hint hint hint</p> <p>Hmmm, wonder why your stomach just started rumbling. 😊 https://t.co/x5LB0fwyLe</p> <p>December is almost over, but there's still PLENTY of time to get your pour on. After all of the festivities are over, take a breath and relax with the \$5 Merry Berry 'Rita. We think you've earned it. https://t.co/mC0kaqp7EF</p>
6	Brand speciality	Introducing specialty foods that represent a brand	<p>Cheesecake is literally in our name. Does that mean we have really freakin' good cheesecake? Yes. But does it mean we have the best cheesecake you've ever had in your entire life? Also, yes. https://t.co/LTkHbLWEhw</p> <p>The Chocolate Caramelicious Cheesecake made with Snickers® is good for when your sweet tooth has a sweet tooth. https://t.co/sJcplBAmxP</p> <p>Got tunnel vision for Tiny Tacos? Our Jackmobile is pulling up soon to help our next fan Recover Harder #SuperJackdMonday https://t.co/kG2mCJ5vNe</p>
7	Warmth conveying	Convoying warmth and love	<p>Is that love in the air? Or pepperoni? Try our Heart Shaped Pizza and a warm, chocolatey brownie. 🍷🍪 https://t.co/4N9DBxVKfG</p> <p>I will be occupied this week with my loved ones https://t.co/YWJrSCiDfY</p> <p>We capital L.O.V.E you @TJOSHIE77. Please be our Valentine 🍷❤️ #LoveDunkin https://t.co/BrPvVNWC4u</p>

8	Calls to purchase	Persuading customers directly to purchase foods	<p>We could all use a GroupNug. Come to the Wendy's drive-thru today and get your free 4pc. nuggets! https://t.co/nCRGbFk4AO</p> <hr/> <p>Now more than ever, we could all use a free Doritos® Locos Tacos. Get yours this Tuesday 3/31 when you visit our drive-thru.</p> <hr/> <p>TODAY we're giving away a new Flamin' Hot Doritos® Locos Tacos for FREE. Drive-thru and grab yours.</p>
9	News sharing	Sharing news around the world and the brands' own news	<p>If @PostMalone was a #Pokémon which one would he be? https://t.co/kYAVTzJY9U</p> <hr/> <p>TEST YOUR BITE. 🍷 Scan to unlock our Papadia Snapchat lens. 📷 https://t.co/GVOUa4twlX</p> <hr/> <p>Texas Roadhouse + Animal Crossing? 🐉 🐉</p>
10	Sense of taste	Estimating customers' perception of taste.	<p>🍩 A donut... but make it SPICY! Introducing the Spicy Ghost Pepper Donut ft. strawberry flavored icing with cayenne & ghost pepper for a sweet heat treat at Dunkin'. 🍷 🍷 Grab one & show your spicy side. 🍷 🍷 https://t.co/dYgBp7eCMj</p> <hr/> <p>A cup of Costa Coffee is slow roasted for a delicious, smooth taste. Strength? We leave that decision to you. Find your preferred blend 🍷 https://t.co/FK3nOISiOH https://t.co/oyKfmiYBFs</p> <hr/> <p>You won't be able to resist falling for our Spicy Garlic Sauce. (See what we did there?) 🍷 https://t.co/FOhlcfkE9n</p>
11	Event promotion	Taking advantage of a specific event to promote	<p>Share your best @WWE Superstar pose using #Sweepstakes and #PJxWWE, as we'll be hosting a #WrestleMania virtual watch party with #WWE. 5 fans will win FREE 📺 for a year along with a WWE Championship Replica Title Belt. Official rules: https://t.co/dxAQTToc3g https://t.co/mbDfh4Nbtw</p> <hr/> <p>#HappyHalloween! The tricks & treats are on us this year & we've got ONE MORE RIDDLE. Here's your final clue. Find the riddle. Solve it. DM us the answer on Twitter for your chance to win \$500 worth of Domino's. 📺 https://t.co/jaOmyWUI5N</p> <hr/> <p>Our favorite matchup of the year. Tune in to our #WrestleMania virtual watch party at 7pm EST #PJxWWE. https://t.co/7AVmTJYFo6</p>
12	Contactless ordering and delivery	Highlighting the contactless ways of ordering and delivery during the COVID-19 pandemic	<p>Contactless ordering for quick and easy pickup. Boom. https://t.co/z4H5Kvz6UF</p> <hr/> <p>Watching the contactless delivery arrive from the window like: *yay* 🍷 🍷 🍷</p> <hr/> <p>Mid-day refresh at your service. #DunkinMatcha Use the Dunkin' App for a contactless way to order and pay 📺 pick up via the drive-thru or carry-out. https://t.co/c3zrvcdV0A</p>

Table 4. Description of the variables used in the predictive modeling.

Variable	Description	Reference
Food type	The rands are divided into six class according to the subsector that they pertain in the catering industry: "Burger/Sandwich", "Casual dining", "Coffee/Dessert", "Fried chicken", "Pizza/Italian food", or "Taco/Mexican food"	(Schultz, 2017)
Published time of tweet	The published time of the tweets, according to the Eastern Standard Time (EST): Morning (from 6:00 to 11:59), Afternoon (from 11:59 to 19:00), or Night (from 19:00 to 5:59)	(Cvijikj & Michahelles, 2013; Imran & Han, 2017; Sabate et al., 2014)
Published day of tweet	The published day of the tweets, according to the Eastern Standard Time (EST): "Monday", "Tuesday", "Wednesday", "Thursday", "Friday", "Saturday", or "Sunday"	(Cvijikj & Michahelles, 2013; Imran & Han, 2017; Sabate et al., 2014; Schultz, 2017)
Media type	The type of the media in a tweet: "No media", "Image", "Gif", or "Video"	(Annamalai et al., 2021; Chandrasekaran et al., 2019; Sabate et al., 2014; Wang & McCarthy, 2021)
Mention	Whether a mention symbol (@) is added in the tweet: "Yes" or "No"	(Liu et al., 2021)
Hash Tag	Whether a hash tag (#) is added in the tweet: "Yes" or "No"	(Araujo et al., 2015)
Link	Whether a link is added in the tweet: "Yes" or "No"	(Annamalai et al., 2021; Chandrasekaran et al., 2019; Sabate et al., 2014; Wang & McCarthy, 2021)
Sentiment	The sentiment in the tweet: "Neutral", "Positive", "Negative", or "Mixed"	(Chandrasekaran et al., 2019)
Topic	The topic extracted from the tweet. For tweets published in normal situation, there are "Food and lifestyle", "Promotion", "Food ordering", "Food delivery", or "Food time". For tweets published in pandemic situation, there are "Food and lifestyle", "Coupons and offers", "Event promotion", "Contactless ordering and delivery", "Food time", "Theme day for foods", "Social responsibility", "Brand speciality", "Warmth conveying", "Calls to purchase", "News sharing", or "Sense of taste".	(Jalali & Papatla, 2019; Zhang et al., 2017)

Table 5. Descriptive statistics of the variables used in the predictive modeling.

Variable	Class	Frequency	Percentage	Class	Frequency	Percentage
		Normal situation			Pandemic situation	
Food type	Burger/Sandwich	818	30.74%	Burger/Sandwich	254	22.74%
	Casual dining	486	18.26%	Casual dining	197	17.64%
	Coffee/Dessert	291	10.94%	Coffee/Dessert	235	21.04%
	Fried chicken	222	8.34%	Fried chicken	55	4.92%
	Pizza/Italian food	530	19.92%	Pizza/Italian food	318	28.47%
	Taco/Mexican food	314	11.80%	Taco/Mexican food	58	5.19%
Published time of tweet	Morning	610	22.92%	Morning	312	27.93%
	Afternoon	1602	60.20%	Afternoon	706	63.21%
	Night	449	16.87%	Night	99	8.86%
Published day of tweet	Monday	429	16.12%	Monday	163	14.59%
	Tuesday	458	17.21%	Tuesday	182	16.29%
	Wednesday	385	14.47%	Wednesday	218	19.52%
	Thursday	434	16.31%	Thursday	169	15.13%
	Friday	391	14.69%	Friday	192	17.19%
	Saturday	273	10.26%	Saturday	97	8.68%
	Sunday	291	10.94%	Sunday	96	8.59%
Media type	No media	1375	51.67%	No media	430	38.50%
	Image	934	35.10%	Image	451	40.38%
	Gif	36	1.35%	Gif	13	1.16%
	Video	316	11.88%	Video	223	19.96%
Mention	No	2294	86.21%	No	880	78.78%
	Yes	367	13.79%	Yes	237	21.22%
Hash Tag	No	1726	64.86%	No	823	73.68%
	Yes	935	35.14%	Yes	294	26.32%
Link	No	892	33.52%	No	322	28.83%
	Yes	1769	66.48%	Yes	795	71.17%
Sentiment	Neural	1802	67.72%	Neural	703	62.94%
	Positive	728	27.36%	Positive	379	33.93%
	Negative	100	3.76%	Negative	23	2.06%
	Mixed	31	1.16%	Mixed	12	1.07%
Topic	Food and lifestyle	498	18.71%	Food and lifestyle	76	6.80%
	Promotion	504	18.94%	Coupons and offers	72	6.45%
	Food ordering	576	21.65%	Event promotion	112	10.03%
	Food delivery	429	16.12%	Contactless ordering and delivery	115	10.30%
	Food time	654	24.58%	Food time	93	8.33%
				Theme day for foods	117	10.47%

				Social responsibility	143	12.80%
				Brand speciality	60	5.37%
				Warmth conveying	74	6.62%
				Calls to purchase	77	6.89%
				News sharing	86	7.70%
				Sense of taste	92	8.24%
Retweet	Retweets < 25	1225	46.04%	Retweets < 25	680	60.88%
volume	Retweets ≥ 25	1436	53.96%	Retweets ≥ 25	437	39.12%
	sum	2661	100.00%	sum	1117	100.00%

Table 6. Metrics of the predictive models.

Situation	Model	Cross-validation		Testing set					
		Accuracy	Kappa	Accuracy	Kappa	Sensitivity	Specificity	PPV	NPV
Normal	SVM	0.702	0.390	0.697	0.383	0.794	0.584	0.691	0.708
	CART	0.668	0.331	0.671	0.339	0.686	0.653	0.699	0.640
	C50	0.701	0.395	0.682	0.358	0.732	0.624	0.695	0.665
	Random forest	0.702	0.389	0.690	0.366	0.801	0.559	0.680	0.706
	Bagged CART	0.662	0.320	0.654	0.304	0.676	0.629	0.681	0.623
	Gradient boosting	0.707	0.406	0.684	0.363	0.718	0.645	0.703	0.661
Pandemic	SVM	0.702	0.357	0.704	0.354	0.517	0.824	0.652	0.727
	CART	0.691	0.344	0.717	0.398	0.598	0.794	0.650	0.755
	C50	0.698	0.349	0.691	0.329	0.517	0.801	0.625	0.722
	Random forest	0.693	0.335	0.726	0.412	0.586	0.816	0.671	0.755
	Bagged CART	0.682	0.327	0.691	0.343	0.575	0.765	0.610	0.738
	Gradient boosting	0.700	0.354	0.726	0.404	0.552	0.838	0.686	0.745