Customer Engagement with Food Companies' Tweets: An investigation of Food Claims and Innovation

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Abstract

As the internet creates platforms for online communication, people start to share their thoughts and attitudes about products on social media platforms, either by commenting or by giving likes to the posts. Given the opportunities of possible conversations between the companies and consumers on social media, companies have been interacting with customers on social medias as a marketing strategy. One well-known social media platform used by many scholars to conduct sentiment analyses of consumers within food sectors is Twitter. In this paper, I study consumers' attitudes towards food companies' tweets analyzing Twitter data from 2019 to 2020. Concepts relating to 'innovation' and food claims are captured using keyword-based analyses. The sentiment analysis is lexicon based, using a lexicon that is specifically designed for social media data. Hypotheses are tested using negative binomial regressions, separately on the 2019 and 2020 data sets. This study shows that both innovation and food claim concepts appear in posts on twitter. Whereas innovation tweets are consistently related to larger numbers of likes, the association of food claims with likes varies.

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1. Introduction

Companies have adopted social media platforms to engage with customers extensively over the past years. Researchers have started to explore these data sources to investigate user and conversations and sentiments in many fields (Vidal et al., 2015, Calheiros et al., 2017).

This study explores twitter conversations in a particular sector – the food sector – and focuses on topics relating to innovation. Although the food sector is not traditionally known to be a highly innovative sector (Acs and Audretsch, 1988), various types of innovation occur frequently, and important features of food products change frequently over time. Therefore, this study investigates the relationship of innovation and specific food claims with user engagement over time.

According to Acs and Audretsch's analysis (1988), the top innovation sectors during the time of their study do not include the food industry by the time the writers' research had been done. Trail (Traill, 1989) also finds the food industry usually defined as "low-tech", "having one of the lowest R&D to sales ratios of any industrial sector." However, the outdated technology level and the small number of innovations are not permanent situations for the food industry. As the food industry is getting more and more technologically advanced (Commission of the European Communities, 1992) according to increasing R&D to sales ratio presented in the article. Yet there is still a gap between food industries and other manufacturing industries (Acosta et al., 2015). The authors supplement that, the gap can be diminished because the great flexibility in production in food industries can stimulate product innovations, and the health and safety improvements are significantly coefficient with process innovations in food industries. While food companies are striving for innovations, they also see the importance of considering marketing. Scholars suggest that companies successfully introduce technologically innovative products to the market by promising the balance and integration between R&D and marketing activities (Burgelman and Sayles, 1988, Grunert et al., 1997)

Consumer involvement is critical for food innovation (Busse and Siebert, 2018). Urban and Hauser first introduced the concept of 'consumer-led product development' as a market-oriented innovation that emphasizes consumer's demands in product innovation (Urban and Hauser, 1993). Customers are getting more aware of food product's quality and safety as the supply of food products in the market is well beyond enough (Earle, 1997, Van Trijp and Steenkamp, 2005). Moreover, the consumer becomes more heterogeneous and their thoughts are more changeable, and thus understanding and predicting customer's tastes and choices can be more difficult (Grunert et al., 1995, Linnemann et al., 1999). My study can help with a further and better understanding of customer's taste/sentiment of food products so that the food companies can have a better idea of what to tweet to attract customers' attention.

Some studies use sentiment analysis to understand consumers' opinions towards food products (Mostafa, 2019, Dixon et al., 2012, Vidal et al., 2016) using Twitter data (users' tweets). Besides, scholars have successfully found the trend indicated by sentiment analysis on Twitter users(Giri et al., 2018). Similarly, I believe the sentiment analysis of tweets can also help with my exploration of the food industry from the perspective of the customers. The gap between existing related research and research in need to better understand consumers' sentiments towards food companies' tweets is nonnegligible. Conclusively, this project means to explore customers' responses towards food company's food tweets and to identify the types of information that attract customers to give likes and show concern.

2. Literature Review

Low and medium technology (LMT) industries are featured by process, organizational and marketing innovation, less competitive internal innovation ability, and by a reliance on external arrangements of equipment, machines, and software (Pavitt, 1984). Different from industries that involve advanced high technologies, the food the industry belongs to the LMT industries. In food industries, there are two primary groups of innovations: R&D associated innovations and customer leading innovations (also called "market-oriented" innovations) (Traill and Grunert, 1997). Product innovation and process innovation are two main categories in food industries (Grunert et al., 1997), and marketing innovations also play an important positive role in both the company's innovation and overall performance (Mothe and Nguyen-Thi, 2008).

2.1 Product Innovation

According to the Oslo Manual, "Product innovations involve significant changes in the capabilities of goods or services. Both entirely new goods and services and significant improvements to existing products are included. (Data, 2005)" Other scholars have defined product innovation as one way of corporate renewal (Dougherty, 1992) and 'engines of renewal' (Bowen et al., 1994). Other scholars also have defined product innovation with three perspectives: a) new to consumers because they believe the product brings new value compared to existing products and the price, b) new to distributors since the new product has innovative 'storage characteristics', 'logistics' and 'contribution to chain positioning', and c) new to producers for new skills developed, resources, etc. (Traill and Grunert, 1997).

Another way to distinguish innovations is to categorize innovations into incremental (evolutionary) and radical (revolutionary) innovations (Traill and Grunert, 1997). Archibugi and his colleagues suggest that food companies are more likely to introduce incremental innovations rather than radical ones, and that food industries are more process innovation-oriented than product-innovation-oriented (Archibugi et al., 1991). Some scholars also define innovations in food industries mostly as moderations of previous products, normally "renewed" "product assortment" (Jongen and Meulenberg, 2005), also known as 'incremental' innovation.

Product innovations can benefit to a great extent from companies' R&D investment for more diversified knowledge (Un et al., 2010). The authors also identify four types of R&D

collaborations that help product innovations in different ways: 1) R&D collaborations with universities provide firms with deeper and more complexed new knowledge. 2) R&D collaborations with competitors benefit product innovations by gaining knowledge from competitors who have a similar knowledge base due to the same or similar customers' needs (Knudsen, 2007). And cooperation with competitors can also reduce duplicated investments and risk (Brandenburger and Nalebuf, 1996). 3) R&D collaborations with suppliers can be helpful because suppliers' knowledge is more specialized, and also because companies and their suppliers have common goals. 4) R&D collaborations with customers since customers can provide their preferences and needs for companies to develop product innovations corresponding to customers' taste, saving much time and avoiding changes that cost money (Koufteros et al., 2005).

However, the performances of food companies in product innovations vary. Different food categories contribute to food innovations distinctively. For example, according to Menrad (2004), dairy and confectionary both contributed 15.8% to the total German food innovations between 1999 and 2001; while pasta and rice only provide 1.2 % of food innovation in total. This can be one reason for if there are many customer's online reviews for a specific category of new food products (food innovations) but only a few in another food category since the number of companies in some food categories do not contribute much. Thus, in the method section, there are details about the creation of the dictionary that contains certain food categories (represented by different positioning claims).

One example of food product innovation are the functional foods, which not only serves as food but also improves health. The term "functional food" and its definition were first introduced in 1984, when the Ministry of Education, Science, and Culture in Japan sponsored a study of new food functions. According to the new food function research, "they (functional foods) lie in a position between conventional foods and medicines, with their use targeting the semi-healthy state of the body generally understood as premonitory to particular diseases (Arai, 1996)." Other countries also have made their attempt in functional foods. For example, the old Chinese book "Shinongbonchokyung " proposed 365 animals, plants, and minerals to be the sources of medicine (Kwak and Jukes, 2001, Hue and Kim, 1997).

Besides Eastern countries, some western countries have also made efforts in the definition of functional foods. The International Life Sciences Institute (ILSI) suggests that food is functional if it demonstrates benefits in one or more target functions in the human body, improves health state, and/or reduces the risk of disease (Action, 1999, Kwak and Jukes, 2001). The Institute of Medicine of the US National Academy of Sciences standardized the definition of functional food to "include any modified food or food ingredient that may provide a health benefit beyond the traditional nutrients it contains" (Anon, 1994).

According to existing literature, dairy, confectionery, soft drinks, bakery, and baby food are categories in which functional foods are developing (Kotilainen et al., 2006, Menrad, 2003). Although it can be difficult to describe the functional foods supply system, Menrad (2003) distinguishes six groups of companies that are in charge of the supply of functional foods in the EU and Germany: 1) "multinational food [companies] with a broad product range," 2) "pharmaceutical and/or dietary products producing companies," 3) "national 'category leaders', " 4) "small and medium-sized companies (SMEs) of the food industry," 5) "retail companies," 6) "supplier of 'functional ingredients' ". Many multinational food companies have R&D departments and sufficient in-house resources, thus can create and develop innovations as functional foods (Weindlmaier, 2000). For the third group, one example of national "category leaders" can be the leading dairy company, Ehrmann, with their ''DailyFit'' dairy products.

2.2 Process Innovation

Although Traill and Meulenberg showed that R&D expenditures are more closely associated with NPD than process innovation (Traill and Meulenberg, 2002), it is important to note that when the firms are selling products to large and/or international markets: NPD is less important than process innovation when the companies are serving customers in large and international markets. Process innovations can reduce the cost of producing existing and new products (Traill and Grunert, 1997).

Process innovation is claimed to be in the later phase of the industry's innovation life cycle, while the rate of product innovation will exceed that of process innovation in the earliest stage of an industry's life (Utterback and Abernathy, 1975). The reason is that, as the industries grow mature, the production systems will be designed and developed to be more efficient, to include better technologies, and thus to be more integrated and automated; while the operating systems will become more under-controlled.

Examples of process innovation can be the application of ultrasonics to get better product quality in extraction processes, compared to the traditional extraction method that may involve toxic, non-recyclable, expensive, and flammable solvents (Cárcel et al., 2012). Besides product and process innovation, marketing innovations are also getting much attention in the development of industries (Chen, 2006).

2.3 Marketing Innovation

Marketing innovations (MI) is defined as "the implementation of new marketing method involving significant changes in product design or packaging, product placement, product promotion or pricing" (OECD. et al., 2005). While other scholars define MI as management of the production process or distribution methods that contain a change in production techniques, equipment, or software (Utkun and Atilgan, 2010).

Leat and Revoredo-Giha (2008) suggest that awareness of the customers is one basic prerequisite of good marketing performance. Therefore, food industries require marketing strategies that follow consumers' changing needs and eating habits as the results of diversified and changeable social as well as economic developments. As the population is growing, the market for functional foods is also growing. Besides, as more people are educated and both partners are busy with jobs, the market of foods that don't require much cooking time and many skills is also growing (Jongen and Meulenberg, 2005), such as the market of snacks, instant foods, and quick-frozen foods. In addition, the population of immigrants grows quickly, so the number of different religions in each country is also increasing rapidly. As a result, foods that are designed for specific religious eating habits are another market trend (Jongen and Meulenberg, 2005). Furthermore, according to Punyatoya (2014), firms can improve consumers' perception and trust of the brand by increasing environmental awareness (EA). And more brand perception and trust are positively associated with purchase intention. Thus, if the brands are environmentally and ecologically friendly, customers are more likely to be loyal to the brands.

Scholars claim that common consumers lack related knowledge and thus are less likely to access health effects (Menrad, 2000, Menrad, 2003) of foods especially functional foods. Yet the authors do not deny the necessity for customers to know the food better and how the food products can help keep them healthy. Besides, consumers can find it hard to change lifestyle and eating habits for functional foods (Hübel et al., 2001, Menrad, 2003). Therefore, the asymmetry of information requires more communication and relevant knowledge dissemination to the customers. Marketing innovation can thus be taken into consideration in solving the information asymmetry of customers towards food products.

Whether marketing strategy functions is subjected to certain criterions: "effectiveness (achieving the intended objectives), efficiency (at minimum cost), and equity (a fair share of the consumer's dollar) " (Jongen and Meulenberg, 2005). One example of marketing innovation is packaging innovation since packaging has become an important marketing tool (Armstrong and Kotler, 2009). Factors that influence food packaging are various. Sonneveld proposed four areas each having different sub-areas (2000).

The first area is business dynamics including mergers or acquisitions, chain integration, material development, and globalization. Sonneveld regards the business dynamics area as the foundation of food packaging. Scholars believe that in the food industry, a "strong partnership" with consumers and end-users of the supply chain under the globalization and internalization trend will be driving the food packaging companies (Madi et al., 1998).

The second area consists of distribution trends with four sub-areas: multinational retailers, market diversification, new ways of selling, and value-added logistics. As E-commerce develops fast and package delivery services stimulated by E-commerce have grown prosperous, the distribution of

packages becomes automatic, fast, and efficient. The packaging of food products thus needs change to be ready for a new way of distribution. One example of packaging innovation to adapt automatic distribution is adhesive palletizing. Adhesive palletizing technology avoids the use of single-use plastics ranging from hot melt and water-based to pressure-sensitive adhesives.
The third area is trends in consumption containing domestic or export, demographics, social environment, and consumption habits. Food products are not only sold domestically but also internationally. Thus, food packaging will also need to change, such as longer shelf-life packaging can help protect and maintain food quality during the export. Besides, because people are living longer, and many are spending less time cooking, food packaging is also adapting to the social changes. Examples are more “easy opening”, “re-closable”, and “dual ovenable packaged meals” packaging (Gerding et al., 1996, Sonneveld, 2000).

The last area is legislative frames including health and safety, environments, and trade barriers. Especially when food products are exported, the differences between local and destination country legislations may cause trade barriers (Sonneveld, 2000). Therefore, negotiation and change in legislation will lead to different packaging of food correspondingly. Sonneveld has also pointed out, another legislation driver of the food packaging industry should be the environmental legislation. To protect the environment, packaging industries are incontestably encouraged to apply re-cycling and reusable materials to food packaging.

Merlino classifies packaging characteristics into visual and verbal elements. Visual elements contain the color, transparency, design, images, material, and size of the packaging; and the verbal group includes nutrition information and slogans (Merlino et al., 2020). For consumers, the packaging of a product sometimes determines their first impression of the quality and value of the product (Olsson and Larsson, 2009). Other scholars also support the significant relationship between customer’s purchase decisions and information on the packaging (Karimi et al., 2013).

In food industries, retailers play an important role by accepting new products. Thus some of the entrepreneurs and innovators fail to bring the new ideas to the market because the retailers do not welcome the new products (Trott and Simms, 2017). However, as the food industry notices the importance of the user/customer’s participation in the innovation process, marketing innovation starts to consider the opinions of the consumers. Researchers believe the interactions between the food industry and the users make it possible for companies to test new ideas and concepts and thus to co-create new products with the customers (Bogers et al., 2010). Therefore, product innovations that involve the customers during the design and experiment process are more likely to be accepted by both the retailers and other customers. Von (2006) has provided examples of selected customers participating as designers in the new product development process.

2.4 Customer and Innovation

As the last three sections have explained, customers play significant roles in product innovation, process innovation, and marketing innovation. Because the purpose of my study is to understand customer's thoughts and the features of those thoughts in food company's innovations, the Total Food Quality Model (Grunert et al, 1996) is crucial to know. The core concept and also the basic idea of the Total Food Quality Model is the "means-end approach to consumer behavior" (Reynolds and Olson, 2001). The "means-end approach" basically means that consumers are not attracted to the product, but what the product can do for them to achieve some goals and how the product can help the customers to attain personal values.

The "cues" in the Total Food Quality Model are the different messages the customers receive to form food quality expectations (Steenkamp, 1990). All concepts including consumers' enjoyment of the food (mainly dealing with the taste of the food), the nutrition contained in the food (mainly dealing with the health aspect of food), and the convenience for cooking, are different types of food quality and they stimulate customers to make up their minds and purchase. Food quality connects the "cues" and "intention to buy." Other scholars have also proposed determinants for customer expectation forming: Grunnet (2004) shows the most common determinant is the visual appearance of products.

Besides the "cues" that affect customers in purchase decision-making, the other side of the Total Food Quality Model sets the base for this study. After customers make their purchase, they respond to show whether the food has met their expectations. And confirmation of whether the food products have met expectations, according to Oliver and colleagues' study (Oliver et al., 1997), is the determinant of whether they will repurchase the products again next time.

Besides the purchasing behaviors of customers, the emotions and sentiment of consumers towards products are also of great importance (Da Silva and Alwi, 2006, Zambardino and Goodfellow, 2007). Yeung and Wyer (Yeung and Wyer Jr, 2005) have proved that customers' emotions are widely used in evaluations of consumers' purchase decisions and post-purchase behaviors. Bowden (2009) also found that consumers' emotions play a non-negligible role in strong consumer-brand relationships.

Social media is one resource that provides what customers feel and think. Some studies have shown that social media is a very helpful and meaningful way to understand consumers' perspectives and thoughts about different aspects of the society and economy (Mostafa, 2013, Yu et al., 2013). Filieri (2013) claims that consumers post their thoughts and opinions towards products on social media and Chua and Banerjee (2013) suggest that social media can be valuable in the marketing management of the customers. Besides, scholars have found that the content of social media posts can be an important source in studies of customers' acceptance of innovations (Dubé et al., 2018). Twitter, as one well-known and widely used social media, has contributed plenty of information and resources for researchers in their studies of consumers' attitudes and sentiments (Park et al., 2016, Tse et al., 2016, D'Avanzo et al., 2017, Bouazizi and Ohtsuki, 2019, Samoggia et al., 2019, Pindado and Barrena, 2020, Samoggia et al., 2020).

2.5 Food Claims and Food Labels

Food claims and food labels provide information about ingredients and nutrients to make it easier for customers to find designated foods (Canada, 2020). Researchers argue that the federal requirements for food labeling can be alleviating the asymmetric information problem of customers (Golan et al., 2001). Another study shows that food labeling helps with the reduction of consumers' intake of selected nutrients, which facilitates the food industries to reduce specific content such as sodium and artificial trans fat in the products (Shangguan et al., 2019).

How do customers respond to the food labels? Research suggests that customers' preferred food labeling schemes are the PDO (Protected Designation of Origin), nutrition information panel, and EU organic logo(Gracia and de-Magistris, 2016). Another study shows that the country and culture of customers determine how customers perceive the quality of foods in terms of food labels and claims (McCluskey and Loureiro, 2003). McCluskey and Loureiro also claim that food claims and labels can be a marketing tool. Nutrition marketing is one marketing method that emphasizes health and nutrition, such as health claims. Research has shown that nutrition marketing is commonly applied with products that have high saturated fat, sodium, and sugar, and also more with products that aim at children than adults (Colby et al., 2010).

2.6 Tweet Features

Scholars identify social media advertising as "any piece of online content designed with a persuasive intent and/or distributed via a social media platform that enables internet users to access, share, engage with, add to, and co-create " (Alhabash et al., 2017) within the public networks of friends, followers and other users (Scott, 2015). Thus, food companies' tweets can be considered as social media advertising.

Shareef and colleagues in earlier days have shown the significant association between advertising values and consumers' attitudes toward social media advertising (Shareef et al., 2019). In addition, Mir (2012) provides supports that customers show favorable attitudes toward posts (advertisements) posted on social media platforms. Furthermore, Williams and Chinn (2010) suggest that companies using social media platforms that help with the presentation of brands and products provide more interaction between companies and the customers, therefore influencing to consumer experience and attitudes.

Twitter, as a social media platform that provides customers opportunities to respond to companies' advertising/tweets, is a good data source to study customers' attitudes towards food companies.

Existing literature has explored the association between certain content elements of tweets and customers' interaction with tweets.

The tone of each tweet can be one element that drives different customers' responses. In a study (Zavattaro et al., 2015) about the association between citizens' involvement and the tone of the US government's tweets, the authors find that tweets with an overall positive tone on Twitter lead to a higher possibility of citizens' interaction with the tweets.

URLs in tweets provide additional information for users to view (Soboleva et al., 2017) and increase the interactivity of social media posts (De Vries et al., 2012). The hashtag in tweets provides users with the discussion of the same topics so they can explore deeper in interesting tweets (Huang et al., 2010). Tweets posted by companies are one form of social media advertisement. And images can help the readers to better recall and interpret the verbal information of the advertisement (Unnava and Burnkrant, 1991). Images/photos included in tweets can also impact the extent of persuasion for customers to make a purchase (McQuarrie and Phillips, 2005). Besides photos, animation(videos) is another kind of virtual information used by web and social media advertisements. The inclusion of videos is likely to increase the click-and-explore intension of customers(Yoo et al., 2004). Furthermore, an existing study has supported that the number of URLs and hashtags bring positive impacts on customer's involvement (likes, retweets, shares, and replies) in the retail industry and that the number of hashtags, videos and pictures, and URLs has a positive influence on customer's involvement (likes, retweets, shares, and replies) (Han et al., 2019b).

According to Craig and Blankenship, using many words rather than one word helps with more persuasive expression because the former allows for moderation and nuance (Craig and Blankenship, 2011). Other scholars also point out that, people can include more concrete and specific terms using many words (Gandarillas et al., 2018). Furthermore, scholars believe that when people are elaborating their emotions and thoughts on something, they are weakening/not showing the original impact of their emotions and thoughts because the additional insights accompanied with their elaborated statements (Pennebaker et al., 2003, Wilson and Gilbert, 2003) or other unnecessary ruminations (Lyubomirsky et al., 2006).

3. Hypotheses

The existing literature studies users by analyzing their reviews on social media, however, very few studies explore how food companies can improve their performance in marketing innovation by studying features of tweets that attract customers. This study thus has focused on answering the following questions:

Research Question 1:
Are positioning claims contained in tweets associated with customer engagement on Twitter?

Research Question 2:
Is the concept of innovation contained in tweets associated with customer engagement on Twitter?

I proposed several hypotheses based on the literature.

Hypothesis 1: Tweets that include the keywords: organic, new, innovative, innovation, kosher, and food are more likely to attract likes.
As the quality of life is getting higher, people are showing more interest in organic foods (Magkos et al., 2006). Researchers have identified awareness and health consciousness as two determinants of customers' intention to purchase organic food (Kapuge, 2016). Thus, food companies' tweets that include the keyword "organic" should have a higher probability of getting likes. Because the existing literature seldom explores customers' perception of the concepts "new," "innovative," and "innovation," and companies are pursuing new and innovative products and services as introduced in the literature review, this study assumes "new," "innovative," and "innovation" to be positive words. Thus, this hypothesis also argues that tweets that have keywords "new," "innovative," and "innovation" tend to be more likely to earn likes. According to Blech (Blech, 2009), Kosher food is produced under specific restrictions for raw materials, production, and packaging. Kosher food is religious and ethical, and kosher food is certified for customers who consider kosher food as a significant factor or condition of purchase. Therefore, this hypothesis assumes tweets that include the keyword "kosher" to be positively associated with the odds of likes. Lastly, food and food choice are seen as key compositions of the expression of identity and culture under different biological, social, economic, and cultural factors (Beardsworth et al, 1997). Besides, one reason why people decide to participate in social media interactions is their self-identity exploration originating from others in the social media community (Ray et al., 2014). People may be more likely to respond to tweets about food because the tweets help them with self-identification. Thus. this hypothesis also argues that tweets contain the keyword "food" are positively associated with the possibility of getting likes.

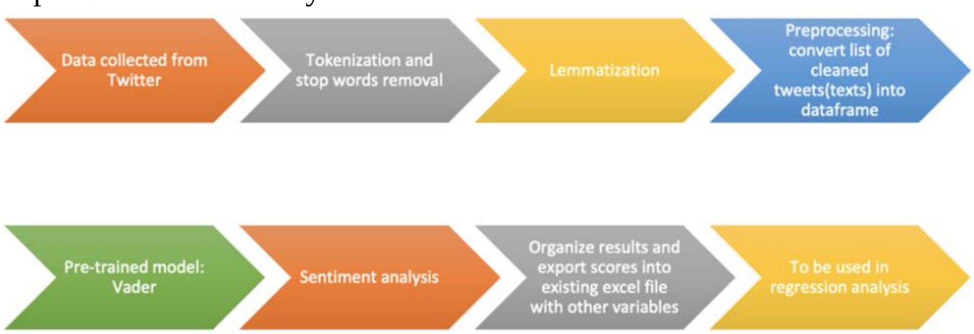
Hypothesis 2: Tweets that contain the keywords: gluten, gmo, allergen, preservative, additive, transfat, cholesterol, and sodium are less likely to earn likes.
According to Minich (2010), gluten can cause serious intestinal disorders and even people who do not have celiac disease can be gluten sensitive. GMOs (genetically modified organisms) are a controversial food type, some point out the toxic effects such as hepatic, pancreatic, renal, or reproductive effects, while the others suggest more clinical trials and animal experiments for the GMOs assessment (Dona and Arvanitoyannis, 2009). This research suggests that mention of GMOs might be negatively perceived by consumers, thus attract less likes. A food allergen can cause serious health issues and food-allergic customers are recommended to follow strict avoidance diets that don't contain allergenic foods and ingredients (Taylor and Hefle, 2006). "Allergen" as the keyword of food allergies is therefore considered as a negative food positioning claim keyword that negatively influences the possibility of tweets getting likes. Artificial food

preservatives such as sodium benzoate (SB) used in foods and soft drinks have been shown to harm memory and motor coordination, and also to increase brain oxidative stress in mice with short-term consumption of the preservative (Khoshnoud et al., 2018). Although natural food preservatives such as sugar and salts do not harm human health (Seetaramaiah et al., 2011), the public common sense regarding artificial preservatives is still negative. This hypothesis considers tweets that include "preservative" to be less likely to earn likes. According to existing research (Christensen et al., 2011, Chen et al., 2015), many customers consider the use of food additives as unwanted and unsafe. To test if there is an unlikable pattern of tweets that contain the word "additive," this hypothesis proposes a negative association between containing "additive" and the possibility of tweets getting likes. Trans fat consumption is considered to be a high-risk factor in causing cardiovascular diseases (Parziale and Ooms, 2019) and thus is hypothesized to have a negative association with tweets getting likes. Cholesterol is another food keyword that worries people. Research (Lupton and Chapman, 1995) finds that people are concerned about their level of cholesterol and look for health advice on diet and cholesterol control, and many people are aware that a high level of cholesterol is detrimental to their health (Goldman et al., 2006). This hypothesis thus considers a negative association between the existence of the keyword "cholesterol" and the likelihood for tweets to obtain likes. The last keyword "sodium" appears to be both a natural preservative and stimulus for salty taste, however, high intake of salt can cause high blood pressure, which can cause stroke and coronary heart disease (He and MacGregor, 2010). According to existing literature, the food industry is investigating ways to contain the same level of salty intensity but less sodium. Hence, Hypothesis 5 suggests a negative association between the existence of the keyword "sodium" and the odds of tweets obtaining likes.

4. Methods

This study is based on a corpus of tweets collected from 2019 and 2020. Graph 1 and the following paragraphs describe the data acquisition, processing, and subsequent statistical analyses.

Graph 1. Sentiment Analysis Process



4.1 Data collection

The study uses the Python to collect tweets, based on a list of enterprises and organizations in the Canadian food sector, collected in the context of a larger project, using seed data sources and additional web searches. The enterprise list contains information such as physical addresses, URLs, and Twitter accounts. The Twitter accounts were primarily obtained from the companies' web sites and were validated to be those of the companies they are associated with, and to be active. Using the Python package 'Twint,' all tweets and retweets by these accounts over the time 2019-2020 time period were then retrieved and automatically stored as Excel files.

There are 532, 661 rows after the steps mentioned in the last paragraph. Because blank tweets do not have a meaningful sentiment score and will interrupt the keyword frequency searching process, I remove 573 rows of the blank tweets. 532,088 rows of valid tweets are prepared for regression analysis.

Because our dataset includes tweets posted in both 2019 and 2020, I decide to divide data into 2019 and 2020 to explore if the same model performs differently on tweets posted in different years. The reason why I divide the data into 2019 and 2020 is that 2020 is the "Covid-19" year and may contain different featured user responses from 2019. I have 251,585 rows of 2019 tweets and 280,473 rows of 2020 tweets. I don't use the left 30 rows because they are 2018 tweets. After manually checking, I found the 30 tweets to be posted near 8:00 pm, December 31, 2018, and the geolocation of the posting to be Vancouver. Because Vancouver has three hours of time lag from the eastern time, those 2018 tweets were posted the midnight of the eastern time which I use to scrape the tweets. And I believe because those 2018 tweets were posted so close to January 1, 2019, they were regarded as 2019 tweets. However, for accuracy, I decide not to use the 30 rows of 2018 tweets.

4.2 Data Cleaning

An important step in this study is to clean and pre-process the individual tweets. The first step is to remove all duplicates by running pandas python codes. Leskovec and his colleagues clean all punctuations marks, non-alphanumeric characters, digits, URL links, mentions to other Twitter users, and "stop words" such as "the", "on", "at" that are meaningless to the expression of information (Leskovec et al., 2020) using the tm package of the R software (Feinerer and Hornik, 2015, Vidal et al., 2015). One method scholars apply to prepare data before cleaning is tokenization (Tse et al., 2016, Liau and Tan, 2014). They then identify meaningful words after breaking up the text content into single words, and check all the misspellings and do the stemming, which is to deduce the prefixes and suffixes to normalized words (Tse et al., 2016, Miner et al., 2012) (e.g. "enjoys", "enjoying", and "enjoyed" transformed into "enjoy").

Refering to the processes applied by researchers mentioned above to prepare data, this study uses csv, nltk, and pandas packages to remove punctuations, tokenize sentences, remove stop words, lemmatize words, reunite the tokenized sentences back as full sentences, and import cleaned data into existing csv files that contain the other independent variables. Note that, I choose lemmatization instead of stemming because lemmatization considers the context of words and is more likely to convert words to the meaningful base form. And stemming generally removes the last several characters of the words, sometimes generating meaningless words and incorrect spellings.

4.3 Sentiment Analysis

Related literature that studies customers' displayed emotions and sentiment online reviews mainly use two methods: content analysis and sentiment analysis. The following content will mainly discuss those two methods applied in the existing literature. Then the discussion of the application of content analysis as well as sentiment analysis is provided.

Twitter data is getting more attention these days from scholars who want to collect data to explore customer-related subjects. An example of existing literature that uses Twitter data and also studies customers' online responses can be the work of Vidal and his colleagues (Vidal et al., 2015). Content analysis helps to determine the existence and frequency of certain words/concepts in texts. The authors first perform content analysis and have two researchers classifying tweets into themes and sub-themes with an inductive coding method (Krippendorff, 2018). To verify the significant differences among different eating situations, the scholars use chi-square tests to evaluate the frequency of each theme and sub-theme. The significant differences evaluation method, chi-square tests can also be applied to this study. Samoggia, Riedel, and Ruggeri (2020) also apply content analysis before sentiment analysis. They adopt a term frequency analysis (TFA) using Nvivo software to define the content of all tweets, repeated tweets, and retweets collected. TFA applies keyword-in-context analysis (KWIC) to create the thematic categories. KWIC is for the consolidation of the categorization. Other scholars (Samoggia et al., 2019) also use Nvivo for content analysis. Because I use python codes to analyze tweets based on keywords, I'm using one form of content analysis. Thus, for this study I apply both the content analysis and the sentiment analysis.

Sentiment analysis is the other method besides content analysis in many studies that analyze online posts. Three scholars who try to analyze hotel online reviews have attempted sentiment analysis in their research (Calheiros et al., 2017). To successfully adopt sentiment analysis, a dictionary of sentiment is important for sentiment analysis. The dictionary compiled by Calheiros and Rita is one example (Table 3. Dictionary for sentiment classification, , 2017). Existing reputable lexicons are the SentiWordNet (Baccianella et al., 2010, Mostafa, 2018), the Q-WordNet (Agerri and García-Serrano, 2010, Mostafa, 2018), the General Inquirer (Stone et al., 1966, Mostafa, 2018), the lexicon of subjectivity clues (Wiebe et al., 2004, Mostafa, 2018), the sentiment-based lexicon (Taboada et al., 2011, Mostafa, 2018), and the LIWC dictionary (Pennebaker et al., 2003, Mostafa, 2018). In Mostafa's study (2018), he chooses the SentiStrength software because it has worked the most successfully in similar research of his work. (Samoggia et al., 2020) also use SentiStrength that applies LIWC dictionary for sentiment analysis in their work. IBM Watson can also help with sentiment analysis and it has a powerful lexicon. Natural language processing (NLP) can be called by python code.

While lexicon-based sentiment analysis is a common method to analyze customers' thoughts for products and services, some scholars argue that the lexicon-based approach including the term frequency method does not consider "semantic word relations, word order and contextual information in the text" (Bansal and Srivastava, 2018). Machine learning is another category of sentiment analysis. Many supervised sentiment analysis algorithms classification such as Support Vector Machines (SVM), Neutral Networks, and Naïve Bayes (Chatzakou and Vakali, 2015, Giatsoglou et al., 2017) are applied in relevant research studies. In Bansal and Srivastava's study that uses the Word2vec model and Neutral Networks, they suggest that CROW learns more quickly and is of higher accuracy than skip-gram. Other supervised algorithms approach such as PAM clustering (Mostafa, 2019), Naive Bayes (NB) (Somantri and Apriliani, 2019), CNN (Abdalla and Özyurt, 2020), and LDA (Mostafa, 2020).

This study decides to use Lexicon-based sentiment analysis. The VADER lexicon is chosen because VADER (Valence Aware Dictionary and Sentiment Reasoner) is a lexicon and rule-based sentiment analysis tool used for sentiments expressed in social media (Hutto and Gilbert, 2014). The two tables below highlight the pros and cons of both Lexicon-based and supervised sentiment analysis. The main reason why this study applies lexicon-based sentiment analysis is that my dataset does not contain labeled data that is required for supervised sentiment analysis.

Table 1. Pros of Lexicon-based and Supervised Sentiment Analysis

Lexicon-based Sentiment Analysis	**Supervised Sentiment Analysis**
No need for labeled data	High accuracy if the most appropriate rule is applied
No need for a learning procedure	No need for a dictionary
Allows for outlier domain	
Easily calculates the sentiment scores	

Table 2. Cons of Lexicon-based and Supervised Sentiment Analysis

Lexicon-based Sentiment Analysis	**Supervised Sentiment Analysis**
Powerful dictionary and linguistic resources required (Devika et al., 2016)	Requires large dataset to get trained

5. Measures

The dependent variable is the number of *likes* of each tweet, which is downloaded directly from Twitter.

The control variables are as follows:

1) *positive, negative, neutral* are three binary control independent variables that represent the sentiment category of each tweet. *positive* has a sentiment score that is larger than 0. *neg* has a sentiment score smaller than 0, and *neu* refers to a sentiment score of 0. The value of each variable can be either 0 and 1, while 0 means no and 1 means yes.
2) Whether there are *url, hashtag, phovideo* included in original tweets are binary control independent variables that represent if a tweet contains url, hashtag, photo, and video. I combine photo and video into one variable because they are higher associated. The value of each variable can be either 0 and 1, while 0 means no and 1 means yes.
3) *length_square* is the square of the number of words compositing into a tweet, numerical control independent variable.
4) *Q12019, Q22019, Q32019, Q42019, Q12020, Q22020, Q32020, and Q42020* are quarters in which the tweet was posted. In one study that tries to predict posts' performance metrics using seven different input features of social media posts, the scholars suggest that months in a manner of seasonality is one relevant feature for the model (Moro et al., 2016). Instead of months, this study uses quarters to explore different month's impacts on the odds of obtaining likes for tweets. These variables are binary control independent. The value of each variable can be either 0 and 1, while 0 means no and 1 means yes.

The focal variables are measured using keyword counts based on groups of terms, which I developed a list of food claims and labels after searching related information online, and the food claim/label variables are chosen from the list.

5) *organic, gluten, gmo, allergen, presertive* (preservative and additive)*, kosher, transfat, cholesterol,* and *sodium* are positioning claim keywords contained in each tweet. These are binary focal independent variables. The value of each variable can be either 0 and 1, while 0 means no and 1 means yes.
6) *new* and *innovative/tion* are two keywords of the innovation concept, binary focal independent variables. The value of each variable can be either 0 and 1, while 0 means no and 1 means yes.
7) *food* is the keyword identified because this study involves Canadian food companies, and *food* is a reasonable keyword for fitting a good model. The value of *food* can be either 0 and 1, while 0 means no and 1 means yes.
8) *covid* is the keyword identified for potential COVID-19 impacts on the data and how the model behaves. The value of *covid* can be either 0 and 1, while 0 means no and 1 means yes.

Generalized Linear Regression Model and Equations

To model the number of likes as a function of the covariates discussed in the previous section, a Negative Binomial GLM with a log link function was used [Equation 1 - 13]. Because this study applied the negative binomial generalized linear regression which uses the log link, the dependent variable in terms of the regression model is the natural log of *likes*.

Equation 1 to Equation 12 use 2019 data and add one focal variable at a time. Equations 13 and 14 uses 2020 data.

$$log(likes_i) = -0.36 + 0.38pos_i + 0.24neg_i + 0.35url_i + 0.59hashtag_i + 1.36phovideo_i - 0.00length\_square_i + 0.04Q12019_i + 0.01Q22019_i - 0.15Q32019_i$$

Equation 1

$$log(likes_i) = -0.36 + 0.38pos_i + 0.24neg_i + 0.35url_i + 0.59hashtag_i + 1.36phovideo_i - 0.00length\_square_i + 0.04Q12019_i + 0.01Q22019_i - 0.16Q32019_i + 0.19organic_i$$

Equation 2

$$log(likes_i) = -0.36 + 0.38pos_i + 0.24neg_i + 0.36url_i + 0.60hashtag_i + 1.36phovideo_i - 0.00length\_square_i + 0.04Q12019_i + 0.01Q22019_i - 0.15Q32019_i + 0.21organic_i - 1.23gluten_i$$

Equation 3

$$log(likes_i) = -0.36 + 0.38pos_i + 0.24neg_i + 0.36url_i + 0.60hashtag_i + 1.36phovideo_i - 0.00length\_square_i + 0.04Q12019_i + 0.01Q22019_i - 0.15Q32019_i + 0.21organic_i - 1.22gluten_i - 0.03gmo_i$$

Equation4

$$log(likes_i) = -0.36 + 0.37pos_i + 0.24neg_i + 0.35url_i + 0.60hashtag_i + 1.36phovideo_i - 0.00length\_square_i + 0.03Q12019_i + 0.01Q22019_i + 0.16Q32019_i + 0.21organic_i - 1.22gluten_i - 0.02gmo_i + 0.21new_i$$

Equation 5

$$log(likes_i) = -0.35 + 0.36pos_i + 0.24neg_i + 0.34url_i + 0.59hashtag_i + 1.35phovideo_i - 0.00length\_square_i + 0.03Q12019_i - 0.00Q22019_i - 0.16Q32019_i + 0.22organic_i - 1.20gluten_i - 0.02gmo_i + 0.21new_i + 0.65innovative/tion_i$$

Equation 6

$$log(likes_i) = –0.35 + 0.35pos_i + 0.24neg_i + 0.33url_i + 0.59hashtag_i + 1.35phovideo_i – 0.00length\_square_i + 0.03Q12019_i – 0.00Q22019_i – 0.16Q32019_i + 0.23organic_i – 1.18b_{10}gluten_i – 0.01gmo_i + 0.21new_i + 0.65innovative/tion_i – 0.82allergen_i$$

Equation 7

$$log(likes_i) = –0.35 + 0.36pos_i + 0.24neg_i + 0.34url_i + 0.59hashtag_i + 1.35phovideo_i – 0.00length\_square_i + 0.03Q12019_i – 0.00Q22019_i – 0.16Q32019_i + 0.23organic_i – 1.18gluten_i – 0.00gmo_i + 0.21new_i + 0.65innovative/tion_i – 0.79allergen_i – 0.61b_{15}presertive_i$$

Equation 8

$$log(likes_i) = –0.35 + 0.35pos_i + 0.24neg_i + 0.34url_i + 0.59hashtag_i + 1.35phovideo_i – 0.00length\_square_i + 0.03Q12019_i – 0.00Q22019_i – 0.16Q32019_i + 0.23organic_i – 1.17gluten_i – 0.00gmo_i + 0.21new_i + 0.65innovative/tion_i – 0.79allergen_i – 0.61presertive_i – 1.04kosher_i$$

Equation 9

$$log(likes_i) = –0.35 + 0.35pos_i + 0.24neg_i + 0.34url_i + 0.59hashtag_i + 1.35phovideo_i – 0.00length\_square_i + 0.03Q12019_i – 0.00Q22019_i – 0.16Q32019_i + 0.23organic_i – 1.17gluten_i – 0.00gmo_i + 0.21new_i + 0.65innovative/tion_i – 0.79b_{14}allergen_i – 0.60presertive_i – 1.04kosher_i – 1.32transfat_i$$

Equation 10

$$log(likes_i) = –0.35+ 0.35pos_i + 0.24neg_i + 0.34url_i + 0.59hashtag_i + 1.35phovideo_i – 0.00length\_square_i + 0.03Q12019_i – 0.00Q22019_i – 0.16Q32019_i + 0.23organic_i – 1.17gluten_i – 0.00gmo_i + 0.21new_i + 0.65innovative/tion_i – 0.79allergen_i – 0.60presertive_i – 1.04kosher_i – 1.14transfat_i – 0.71 cholesterol_i$$

Equation 11

$$log(likes_i) = –0.35 + 0.35pos_i + 0.24neg_i + 0.33url_i + 0.59hashtag_i + 1.35phovideo_i – 0.00length\_square_i + 0.03Q12019_i – 0.00Q22019_i – 0.16Q32019_i + 0.23organic_i – 1.17gluten_i – 0.00gmo_i + 0.21new_i + 0.65innovative/tion_i – 0.79allergen_i – 0.60presertive_i – 1.03kosher_i – 1.02transfat_i – 0.59cholesterol_i – 0.44sodium_i$$

Equation 12

$$log(likes_i) = –0.35 + 0.35pos_i + 0.24neg_i + 0.33url_i + 0.60hashtag_i + 1.35phovideo_i – 0.00length\_square_i + 0.02Q12019_i – 0.00Q22019_i – 0.16Q32019_i + 0.23organic_i – 1.15gluten_i – 0.00gmo_i + 0.20new_i + 0.65innovative/tion_i – 0.77allergen_i – 0.60presertive_i – 1.01kosher_i – 0.92transfat_i – 0.60cholesterol_i – 0.43sodium_i – 0.21food_i$$

Equation 13

$$log(likes_i) = 4.48 – 0.28 pos_i + 0.14neg_i – 1.26url_i – 0.68hashtag_i + 0.46phovideo_i – 0.00length\_square_i – 0.96Q22020_i – 1.02Q32020_i – 1.12Q42020_i$$

Equation 14

$$log(likes_i) = 4.49 – 0.30pos_i + 0.13neg_i – 1.24b_2url_i – 0.65hashtag_i + 0.45phovideo_i – 0.00length\_square_i – 0.93Q22020_i – 1.01Q32020_i – 1.12Q42020_i – 0.55organic_i – 1.33gluten_i – 1.25gmo_i – 0.08new_i + 0.81innovative/tion_i – 1.17allergen_i – 1.18presertive_i – 1.51kosher_i – 2.73transfat_i – 2.19cholesterol_i – 1.47sodium_i – 0.03food_i – 0.64covid_i$$

Equation 15

6. Results

In the first subsection "Results by Year", I will present my results of models from Equation 1 to 15, using all data in 2019 and 2020 separately. In the next subsection "Results by Reference to Innovation", I will show the results from Equation 16 to 19 which are using the 'Innovation & Innovative' data.

6.1 Results by Year

We first run Equation 1 that includes only the control variables. The VIFs of all variables in Equation 1 are no bigger than 3 as shown in Table 4, which suggests that Equation 1 does not display issues relating to multicollinearity. To find the best fit model, I run different models with one focal variable added at a time and compare the deviance [Table 5]. As shown in Table 5, Equation 1 to Equation 13, when I add more variables to the basic model using 2019 data, the deviance keeps decreasing. And the decreasing deviance means more variables adding to the model makes the model fit better.

The control independent variable *length_square* is statistically in every equation, meaning that using both 2019 and 2020 data, there is no association between the square of the length of each tweet and the odds of getting likes.

As shown in Equation 1 [Table 3], *positive, negative, url, hashtag, phovideo* are all positively associated with *likes*. The first quarter *Q12019* has a positive association with the number of likes, and the third quarter shows a negative sign. The coefficient of the second quarter of 2019 is not statistically significant. Equation 2 and Equation 1 have all variables in the same sign, except Equation 2 has additional variable *organic.* The coefficient 0.19 of *organic* in Equation 2 suggests that the existence of the keyword "organic" increases the odds for each tweet to get likes by 0.19. Equation 3 adds new variable *gluten*, which has a negative coefficient of -1.23. Notice the coefficients of *url, hashtag,* and *organic* increase by 0.01, 0.01, and 0.02, suggesting *url, hashtag,* and *organic* are negatively associated with *gluten*. Also, adding *gluten* to the model leads to a decrease in deviance from 474,240 to 472,860 (see Table 3, Equation 3), which is a relatively significant decrease.

Equation 4 adds variable *gmo*. However, the coefficient of *gmo* is not statistically significant because it has a p-value (0.534) that is greater than 0.05. From Equation 4 to Equation 13, *gmo* is always not statistically significant. The signs of other variables are almost the same in both Equation 4 and Equation 3. Equation 5 has new variable *new*, which has a coefficient of 0.21. The positive coefficient shows a positive association between the existence of the keyword "new" and the likelihood of getting likes. Equation 6 adds variable *innovative/tion*, which has a positive coefficient of 0.65. The coefficient shows that a tweet that includes keyword "innovative" and "innovation" are more likely to receive likes. Note that *innovative/tion* decreases the deviance of the model from 472,170 to 470,640 (see Table 3, Equation 6), the other variable that makes the model fit much better besides *gluten*. In addition, the coefficient of *Q22019* is not statistically significant. The sign of *Q32019* changes from positive [Equation 5] to negative [Equation 6], implying a positive association between whether tweets are posted in the third quarter (July to September) and whether tweets contain the keyword “innovative” and “innovation. Equation 7 adds variable *allergen*, which has a coefficient of –0.82, suggesting a negative association between if a tweet contains the keyword “allergen” and the probability of getting likes. Equation 8 adds variable *presertive*, which has a coefficient of –0.61, referring to a negative association between whether a tweet contains the keyword “preservative” and “additive” and the possibility of earning likes. Equation 9 adds variable *kosher*, which has a coefficient of –1.04, suggesting a negative influence. Equation 10 has *transfat* as the new variable. The variable *transfat* has a coefficient of –1.32, representing a negative association between having the keyword “transfat” and the likelihood of getting likes. Equation 11 adds *cholesterol*, which has a coefficient of –0.71, suggesting a negative influence on the probability of obtaining likes. Notice that, adding *cholesterol* weakens the negative influence of *transfat*. Equation 12 adds *sodium* that has a coefficient of –0.44, showing tweets that contain the keyword “sodium” have a negative influence on the likelihood of getting likes. Equation 13 has additional variable *food*. The variable *food* has a negative coefficient of –0.21, suggesting its negative impacts on how likely the tweets get likes.

Equation 13 [Table 3] shows the results of the GLM regression analysis on the equation that includes all variables using 2019 Twitter data. The coefficients of *pos* and *neg* are positive, suggesting that when the tone of tweets is positive and negative compared to the neutral tone, the tweets are more likely to obtain likes. Hypothesis 1 is partially supported because besides *pos*, *neg* is also positively associated with the odds of likes. *url* is also positively associated with the probability of getting likes. The variables *hashtag* and *phovideo* have positive coefficient as well, implying that food companies’ tweets which contain hashtag or photo and video tend to be more likely to earn likes. Hypothesis 2 is thus supported that tweets that contain url, hashtag, photo, and video are likely to obtain likes. The study fails to support Hypothesis 3 because *length_square* is not statistically significant.

Variables *organic, new, innovative/tion* are positively associated (0.23, 0.20, 0.65) with the odds of the number of likes, thus Hypothesis 4 is partially supported. Variables *kosher* and *food* are expected to be positively associated with the number of likes, however the opposite. Hypothesis 5 is mostly supported: *allergen* (–0.77), *presertive* (–0.60), *transfat* (–0.92), *cholesterol* (–0.60), *sodium* (–0.43) are all negatively associated with the odds of getting likes. Variable “gmo” is the exception and is not statistically significant as shown in the results [Table 3, Equation 13].

Equations 14 and 15 are using 2020 data. Table 6 shows the GLM regression results of 2020 models with only control variables and with all variables. Different from 2019 equations, the 2020 basic equation [Table 6, Equation 14] shows a negative association (–0.28) between *positive* and the number of likes. *url* (–1.26) and *hashtag* (–0.68) are also showing negative coefficients compared to the positive coefficient in 2019 data. Besides, the last three quarters of 2020 show a negative association between tweets posted in those quarters and the likelihood of attracting likes (–0.96. –1.02, and –1.12). The only positive coefficients belong to *neg* and *photo and video*, 0.14 and 0.46. All control variables of Equation 15 have the same signs as they do in Equation 14. Different from 2019 equations, the 2020 full-variable model [Table 6, Equation 15] has all food positioning claim variable negative signed. *Organic* (–0.55), *gluten* (–1.33), *gmo* (–1.25), *allergen* (–1.17), *presertive* (–1.18), *kosher* (–1.51), *transfat* (–2.73), *cholesterol* (–2.19), and *sodium* (–1.47). Additionally, *food* has the same negative sign as it does in 2019 equations, unexpectedly. The variable *covid* is identified because COVID-19 is the topic and theme of most of 2020. The negative coefficient (–0.64) of *covid* suggests that tweets that contain the keyword "covid" are negatively associated with the possibility of getting likes. The coefficient of *new* is –0.08, suggesting a light influence of the keyword "new" on the odds of getting likes. Variable *innovative/tion* demonstrates the same positive sign as it does in 2019 equations, illustrating a positive influence on the probability of obtaining likes.

Table 3. Negative Binomial Generalized Linear Model Regression Results of Equation 1-13, 2019

Variable / Equation	1	2	3	4	5	6	7	8	9	10	11	12	13
Constant	-0.36	-0.36	-0.36	-0.36	-0.36	-0.35	-0.35	-0.35	-0.35	-0.35	-0.35	-0.35	-0.34
	0	0	0	0	0	0	0	0	0	0	0	0	0
Positive	0.38	0.38	0.38	0.38	0.37	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36
	0	0	0	0	0	0	0	0	0	0	0	0	0
Negative	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24
	0	0	0	0	0	0	0	0	0	0	0	0	0
Url	0.35	0.35	0.36	0.36	0.35	0.34	0.34	0.34	0.34	0.34	0.34	0.33	0.33
	0	0	0	0	0	0	0	0	0	0	0	0	0
Hashtag	0.59	0.59	0.6	0.6	0.6	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.6
	0	0	0	0	0	0	0	0	0	0	0	0	0
hoto or Vide	1.36	1.36	1.36	1.36	1.36	1.35	1.35	1.35	1.35	1.35	1.35	1.35	1.35
	0	0	0	0	0	0	0	0	0	0	0	0	0
ength (squa	0	0	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0	0	0
Q12019	0.04	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02
	0	0	0	0	0	0	0	0	0	0	0	0	0
Q22019	0.01	0.01	0.01	0.01	0.01	0	0	0	0	0	0	0	0
	(-0.13)	(-0.14)	(-0.12)	(-0.12)	(-0.29)	(-0.83)	(-0.83)	(-0.82)	(-0.82)	(-0.82)	(-0.83)	(-0.83)	(-0.62)
Q32019	-0.15	-0.16	-0.15	-0.15	-0.16	-0.16	-0.16	-0.16	-0.16	-0.16	-0.16	-0.16	-0.16
	0	0	0	0	0	0	0	0	0	0	0	0	0
Organic	-	0.19	0.21	0.21	0.21	0.22	0.23	0.23	0.23	0.23	0.23	0.23	0.23
		0	0	0	0	0	0	0	0	0	0	0	0
Gluten	-	-	-1.23	-1.22	-1.22	-1.2	-1.18	-1.18	-1.17	-1.17	-1.17	-1.17	-1.15
			0	0	0	0	0	0	0	0	0	0	0
GMO	-	-	-	-0.03	-0.02	-0.02	-0.01	-0.01	0	0	0	0	0.01
				-0.53	(-0.60)	(-0.68)	(-0.81)	(-0.86)	(-0.94)	(-0.98)	(-0.99)	(-0.99)	(-0.74)
New	-	-	-	-	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.2
					0	0	0	0	0	0	0	0	0
tive and Inn	-	-	-	-	-	0.65	0.65	0.65	0.65	0.65	0.65	0.65	0.65
						0	0	0	0	0	0	0	0
Allergen	-	-	-	-	-	-	-0.82	-0.79	-0.79	-0.79	-0.79	-0.79	-0.77
							0	0	0	0	0	0	0
vative and A	-	-	-	-	-	-	-	-0.61	-0.61	-0.6	-0.6	-0.6	-0.6
								0	0	0	0	0	0
Kosher	-	-	-	-	-	-	-	-	-1.04	-1.04	-1.04	-1.03	-1.01
									0	0	0	0	0
Trans Fat	-	-	-	-	-	-	-	-	-	-1.32	-1.14	-1.02	-1.92
										0	0	0	0
Cholesterol	-	-	-	-	-	-	-	-	-	-	-0.71	-0.59	-0.6
											0	0	0
Sodium	-	-	-	-	-	-	-	-	-	-	-	-0.44	-0.43
												0	0
Food	-	-	-	-	-	-	-	-	-	-	-	-	-0.21
													0

Table 4. VIFs of Equation 1

Variable	VIF
pos	3.00
neg	1.22
url	1.56
hashtag	2.06
phovideo	1.93
length_square	2.67
Q12019	1.56
Q22019	1.60
Q32019	1.53

Table 5. Deviance and Chi2 of Equation 1 - 15

Equation	Deviance	Chi2
1	474,340	29,100,000
2	474,240	29,100,000
3	472,860	29,000,000
4	472,860	29,000,000
5	472,170	29,100,000
6	470,640	29,100,000
7	470,610	29,100,000
8	470,590	29,100,000
9	470,570	29,100,000
10	470,560	29,100,000
11	470,540	29,100,000
12	470,530	29,100,000
13	469,950	28,700,000
14	1,381,100	371,000,000
15	1,372,600	357,000,000

Table 6. Negative Binomial Generalized Linear Model Regression Results of Equation 14-15, 2020

Variable \ Equation	14	15
Constant	4.48 (0.00)	4.49 (0.00)
Positive	-0.28 (0.00)	-0.30 (0.00)
Negative	0.14 (0.00)	0.13 (0.00)
Url	-1.26 (0.00)	-1.24 (0.00)
Hashtag	-0.68 (0.00)	-0.65 (0.00)
Photo or Video	0.46 (0.00)	0.44 (0.00)
Length (square)	0.00 (0.00)	0.00 (0.00)
Q22020	-0.96 (0.00)	-0.93 (0.00)
Q32020	-1.02 (0.00)	-1.01 (0.00)
Q42020	-1.12 (0.00)	-1.11 (0.00)
Organic	-	-0.55 (0.00)
Gluten	-	-1.33 (0.00)
GMO	-	-1.25 (0.00)
New	-	-0.08 (0.00)
Innovative and Innovation	-	0.81 (0.00)
Allergen	-	-1.17 (0.00)
Preservative and Additive	-	-1.18 (0.00)
Kosher	-	-1.51 (0.00)
Trans Fat	-	-2.73 (0.00)
Cholesterol	-	-2.19 (0.00)
Sodium	-	-1.47 (0.00)
Food	-	-0.03 (0.00)
Covid	-	-0.64

6.2 Results by Reference to Innovation

After I find that *innovative/tion* has positive coefficients in models of both 2019 and 2020, different from other focal independent variables in the equations, I decide to run the following models using 2019 and 2020 data with tweets that have and not have keywords “innovative” and “innovation.” The purpose of the additional regressions is to find out if tweets that contain keywords “innovative” and “innovation” are associated with other defined focal variables. Equations 16 and 17 use 2019 data, the formal using “innovative” and “innovation” data while the latter not. Equations 18 and 19 applied on 2020 data, the formal using “innovative” and “innovation” data and the latter not.

Because 2019 "innovative" and "innovation" data has no tweets that contain keywords "transfat," "cholesterol," and "sodium," 2019 Equations 16 and 17 do not contain focal variable *transfat, cholesterol,* and *sodium.* Besides, since Equations 16-19 are using "innovative" and "innovation" data, variable *innovative/tion* is removed from the four equations. Equations 16 and 17 also do not contain control variable *length_square* because it has high VIF and causes multicollinearity problems.

Since 2020, "innovative" and "innovation" data has no tweets that include keywords kosher, transfat, cholesterol, sodium, and allergen, corresponding focal variables are removed from Equations 18 and 19. Additionally, *length_square* has a VIF of 5 and causes multicollinearity, thus removed as well.

$$log(likes_i) = -1.5 + 1.05pos_i + 0.95neg_i + 0.90url_i + 0.77hashtag_i + 1.08phovideo_i + 0.29Q12019_i + 0.37Q22019_i - 0.12Q32019_i - 0.90organic_i - 0.89gluten_i - 0.25gmo_i + 0.29new_i - 22.85allergen_i - 23.99presertive_i - 22.96kosher_i - 0.62food_i$$

Equation 16

$$log(likes_i) = -0.35 + 0.32pos_i + 0.20neg_i + 0.31url_i + 0.59hashtag_i + 1.30phovideo_i + 0.02Q12019_i - 0.1Q22019_i - 0.16Q32019_i + 0.21organic_i - 1.16gluten_i + 0.01gmo_i + 0.19new_i - 0.79allergen_i - 0.61presertive_i - 1.01kosher_i - 0.22food_i$$

Equation 17

$$log(likes_i) = -1.74 + 1.82pos_i + 1.87neg_i + 0.85b_2url_i + 1.12hashtag_i + 0.72phovideo_i 45phovideo_i + 0.00length\_square_i - 0.27Q22020_i - 0.59Q32020_i - 0.56Q42020_i - 0.74organic_i + 0.5gluten_i - 1.01gmo_i - 0.1new_i - 2.23presertive_i - 0.13food_i - 0.54covid_i$$

Equation 18

$$log(likes_i) = 4.49 - 0.30pos_i + 0.13neg_i - 1.26b_2url_i - 0.65hashtag_i + 0.42phovideo_i - 0.00length\_square_i - 0.93Q22020_i - 1.01Q32020_i - 1.11Q42020_i - 0.54organic_i - 1.40gluten_i - 1.26gmo_i - 0.07new_i - 1.17presertive_i - 0.01food_i - 0.63covid_i$$

Equation 19

Table 7. Negative Binomial Generalized Linear Model Regression Results of Equation 16-17, 2019

Variable / Equation	16	17
Constant	-1.50 (0.00)	-0.35 (0.00)
Positive	1.05 (0.00)	0.32 (0.00)
Negative	0.95 (0.00)	0.20 (0.00)
Url	0.90 (0.00)	0.31 (0.00)
Hashtag	0.77 (0.00)	0.59 (0.00)
Photo or Video	2.08 (0.00)	1.30 (0.00)
Q12019	0.29 (0.00)	0.02 (0.00)
Q22019	0.37 (0.00)	-0.10 (0.10)
Q32019	-0.12 (0.04)	-0.16 (0.04)
Organic	-0.90 (0.00)	0.21 (0.00)
Gluten	-0.89 (0.12)	-1.16 (0.12)
GMO	-0.25 (0.52)	0.01 (0.80)
New	0.29 (0.00)	0.19 (0.00)
Allergen	-22.85 (1.00)	-0.79 (1.00)
Preservative and Additive	-23.99 (1.00)	-0.61 (1.00)
Kosher	-22.96 (1.00)	-1.01 (1.00)
Food	-0.62 (0.00))	-0.22 (0.00)

Table 8. Negative Binomial Generalized Linear Model Regression Results of Equation 18-19, 2020

Variable / Equation	18	19
Constant	-1.74 (0.00)	4.49 (0.00)
Positive	1.82 (0.00)	-0.30 (0.00)
Negative	1.87 (0.00)	0.13 (0.00)
Url	0.85 (0.00)	-1.26 (0.00)
Hashtag	1.12 (0.00)	-0.65 (0.00)
Photo or Video	0.72 (0.00)	0.42 (0.00)
Length (square)	0.00 (0.00)	-0.00 (0.00)
Q22020	-0.27 (0.00)	-0.93 (0.00)
Q32020	-0.59 (0.00)	-1.01 (0.00)
Q42020	-0.56 (0.00)	-1.11 (0.00)
Organic	-0.74 (0.00)	-0.54 (0.00)
Gluten	1.5 (0.00)	-1.40 (0.00)
GMO	-1.01 (0.02)	-1.26 (0.00)
New	-0.10 (0.06)	-0.07 (0.00)
Preservative and Additive	-2.23 (0.01)	-1.17 (0.00)
Food	-0.13 (0.02)	-0.01 (0.21)
Covid	-0.54 (0.00)	-0.63 (0.00)

Comparing the results [Table 7], *positive, negative, url, hashtag, phovideo (photo and video), Q12019* all have the same positive association with the number of likes. *Q22019* is positive in Equation 16 and negative in Equation 17. However, *Q22019* is not statistically significant in Equation 17, thus the difference in signs is not meaningful. *Q32019* is both negative in Equations 16 and 17. *Organic* has a negative coefficient of –0.90 in Equation 16, nevertheless a positive coefficient of 0.21 in Equation 17. *gluten* has negative coefficients in both Equations 16 and 17. Focal variable *gmo* although has different sign of coefficients, not statistically significant according to its p-values (0.52, 0.80). The coefficients of focal variable *new* is positive in both Equation 16 and 17. Focal variables *allergen, presertive*, *kosher*, and *food* all have negative coefficients in both Equations 16 and 17.

Looking at the results shown in Table 8, the coefficient of *positive* in “innovation” and “innovative” data is positive (1.82), but negative (–0.30) in the equation using the opposite dataset.

7. Discussion and Implications

By studying tweets and the different features of the tweets, this study provides insights into customers' preferences in food companies' tweets and the importance of the concept "innovation" in attracting more likes for food companies in posting tweets. Most of the focal variables are significant.

First, the results of Equation 13 including all variables using 2019 Twitter data show that tweets which are positive and negative toned are likely to earn likes. Hypothesis 1 is partially supported because the positive impacts that negative tone can have on the probability of getting likes were not expected. For future tweets, companies may want to show clear sentiment, either negative or positive, to increase the likelihood of getting more likes. Plus, since Hypothesis 2 is supported, that tweets that contain urls, hashtags, photos, and videos have a higher probability to earn likes in contrast with tweets that do not. Companies are recommended to include urls, hashtags, photos, and videos media to attract more attention. Surprisingly, the insignificant negative association between *length_square* and the odds of likes does not support Hypothesis 3, and thus further related analyses are expected.

Second, Table 3 shows that Hypothesis 4 is partially supported. The coefficients of *organic, new, innovative/tion* are all positive and each suggests a positive association between having the word in tweets and the likelihood of getting likes. However, *kosher* and *food* are negatively associated with the odds of number of likes, hence more research to validate the negativity and to explore the reasons are suggested. Based on the results of Hypothesis 4, I recommend companies to include keywords "organic," "new," "innovative" and "innovation" in future tweets to increase the probability of getting likes. Hypothesis 5 is mostly supported by the results [Table 3]. The variable *gmo* is not statistically significant, so more research to validate the negative association between whether a tweet contains the keyword "gmo" and the odds of getting likes is needed. Based on the 2019 results of Hypothesis 5, companies are recommended to investigate more on the expression of content that is related to "allergen," "preservative," "additive," "transfat," "cholesterol," and "sodium" to create a higher possibility for their tweets to get likes.

Third, Table 6 shows the regression results of 2020 Twitter data. By comparing the coefficients of Equation 15 with Equation 13, I obtain surprising findings. The positive tone of the tweet in 2020 is no longer positively associated with the odds of getting likes as in 2019. One possible reason can be the COVID-19 influence on the entire tone of tweets, to be negative. Besides, variable *neg* has both positive coefficients in the 2019 and 2020 equations. The existing literature suggests that individuals are leaning towards negative news and are easily attracted by negative online news in contrast with positive news (Han et al., 2019a). Thus, the reason why negative toned tweets are positively associated with the odds of likes in 2019 and 2020 can be that people are more into negative news and tweets. In addition, different from 2019 equations, 2020 equations show negative signs of *url* and *hashtag* coefficients. There is little literature explaining the negative influence of urls and hashtags on tweets getting likes, but mostly positive influence.

Fourth, Equation 15 has shown negative coefficients of all food positioning claims including those that are expected to be negative: gluten, gmo, allergen, preservative, additive, trans fat, cholesterol, sodium, and those that are expected to be positive: organic and food. The study has not explored if the COVID-19 is influencing the impacts of positioning claim keywords on the probability of getting likes and therefore cannot conclude the reasons for the negativity. However, future research on finding the reasons is welcomed. Furthermore, the keyword "covid" has shown a negative influence on the odds of getting likes [Equation 15]. Some literature has suggested people's interest in negative news, and covid is the keyword of the pandemic. Future studies on the validation of keyword "covid's negative influence on the number of likes and reason behind are promoted.

Fifth, the coefficient of variable *innovative/tion* has stayed positive in both 2019 and 2020 equations, implying a positive influence on the odds of attracting likes for tweets. Existing literature mainly studies companies' emphasis on innovations involving research on customers and customer orientation. However, studies rarely investigate customers' opinions with innovations, and within the background of this study, food innovations. This study has supported a positive relationship between tweets that contain keywords "innovative" and "innovation" and the odds of getting likes using both 2019 and 2020 Twitter data.

Comparing 2019 "innovative" / "innovation" data with 2019 non "innovative" / "innovation" data, *organic* is negatively associated with the possibility of getting likes using "innovative" / "innovation" data, however, has a positive coefficient in non "innovative" / "innovation" data. The difference implies that among tweets that contain keywords "innovative" and "innovation," if the tweets also contain "organic," the tweets are less likely to obtain likes. One thought behind this finding is that people may experience aesthetic fatigue (tiredness caused by too much exposure of a concept or an object) when food companies tweet about "organic." "Organic" as a product innovation concept in the food industry, appears to be one food trend that food companies are pursuing and advertising about (Baourakis, 2004). Besides, the premium in the price of organic foods is also blocking many consumers (Aschemann-Witzel and Zielke, 2017). That being said, many companies are promoting the concept of "organic" which leaves consumers insensitive to the new food concept, while the prices are incredibly high. Thus, companies need to take care of their corporate ability (CA) image and corporate social responsibility (CSR) image. Yu et al. have found that organic food companies can effectively facilitate consumer trust, continuous purchase, and active participation in the co-design and co-development of new products by taking good care of their CA and CSR (Yu et al., 2021).

Comparing 2020 "innovative" / "innovation" data with 2020 the opposite dataset, tweets that have a positive tone have a higher probability to earn likes. Nonetheless, positive tweets in non "innovative" / "innovation" data are negatively correlated with the odds of getting likes. The comparison implies that Tweets that contain keywords "innovative" and "innovation" and are using a positive tone are more likely to get likes, but the tweets are less likely to obtain likes when tweets do not include the innovation concept and also are positive. The reason may be that, in 2020, if users are fond of the concept of innovation, they are also more likely to like positive tweets. The same reason can also apply to why *url, hashtag,* and *gluten* are presenting positive coefficients but negative ones when the data is 2020, non "innovative" / "innovation."

8. Limitations

This study uses the number of likes of each tweet to learn about customers' attitudes towards companies' tweets, thereby finding out the elements of each tweet that create the most-liked tweets. However, users who give likes to a tweet may not be the customers. Besides, the behavior of giving likes does not necessarily signal a positive attitude. Furthermore, researchers have shown that some of the online reviews are fake or do not relate to the products (Liu et al., 2017). Following this logic, the motivation for customers to give likes may not be relevant to the products, however, maybe the color of the picture, for example. Those aspects are not met during the entire research process. Thus, to better and more accurately understand customers or potential customers' attitudes towards food companies' tweets, a complementary survey method is recommended. So that whether a customer is positive or negative towards the tweets can be identified without ignoring the effects caused by behaviors of giving likes not because of enjoyment.

In addition, paid online reviews can skew the results. Duan et al. found that the volume of online reviews has a positive impact on box office revenue (Duan et al., 2008). Other scholars also support the association between more online reviews and product sales (Ghose and Ipeirotis, 2010). Products that have few comments and reviews are thus less likely to encourage buying behaviors. There are many online crowdsourcing sites such as Amazon Mechanical Turk to help companies recruit workers to give reviews of their products. However, paid online reviews are not always biased or meaningless, as long as appropriate methods are applied during the paid reviewing process. Wang et al. suggest that added disclosure text (to inform others that compensation has been received for a review), higher payment, and flexibility to select products to review can lead to high-quality reviews (Wang et al., 2012). Overall, some paid online reviews can be informative and helpful, while the others are not and thus cause bias in the results of this study.

9. Contributions

This study has firstly contributed to food industry research and development by providing methods as the reference for future researchers. Besides, this study also inspires food companies to involve social media to interact with customers by demonstrating the association between keywords involved in tweets and the number of likes. Tweets that contain food claim "organic" are likely to attract more likes. Keywords "new," "innovation," and "innovative" also play nonnegligible roles in helping tweets obtain likes. Companies should consider how the involvement of those keywords impacts their marketing performance in social media advertising. Food labels “allergen,” “preservative,” “additive,” “transfat,” “cholesterol,” and “sodium” are supported by the results to show negative influence on the number of likes obtained by the tweets that contain those words. Because there can be some phrases that are composed of prefix “non-” and those “negative food labels,” future studies can complement this study by including the “non-” prefixed food claims phrases to see if “non-” negative food claims show positive impacts on the number of likes.

According to an existing study (Trott and Simms, 2017), innovations in the food industry have to be accepted by retailers. When the retailers are not satisfied, the products will fail before they make it to the shelf. If the companies can relate it better to their customers and they have feedback from their customers and predicted results based on the feedback, they can show the information to the retailers. Thus, the retailers might be more easily persuaded to accept the product.

Also, Leat and Revoredo-Giha (2008) claim that the prerequisite of good marketing performance is the awareness of customers. The number of likes of tweets can be one measurement/indicator of the awareness of customers. As companies invest more in R&D about other features and keywords that may attract more likes, they will possibly increase the awareness of consumers and then perform better in the market.

In addition, according to Jongen and Meulenberg (2005), food that relates to specific religious eating habits can be a trend in the food industry as the immigrant population is getting larger. This study chooses “kosher” as one of the keywords and finds the association between the existence of the keyword “kosher” and the number of likes. Hence, future studies can explore further evidence in the trend of food for certain religious/cultural eating habits based on the contribution this study has made.

10. Future Research

Future study can test the interactions between different food claims. For example, if Twitter users who are less likely to like “gluten” tweets will be more likely to like tweets that contain keywords “organic” or special elements such as urls and hashtags.

This study also highlighted substantive differences between the year 2019 and 2020, suggesting relationships between food claims and customer engagement may be variable over time. Future research investigating changes over time and relating them to news, food policies, and trending food innovations at times is recommended. In addition, because 2019 and 2020 (COVID-19 event) data have a different sign for *positive*, the positive tone of the tweets, more research is needed to validate if the pandemic is causing people’s preference to liking negative tweets. Additionally, 2020 equations show negative coefficients for *url* and *hashtag*, which according to the existing literature is not expected. Thus, I suggest future researchers explore the potential negative impacts that urls and hashtags can cause on the likes of tweets. Furthermore, tweets that contain the concept of innovation and also positive have a higher possibility to get likes, and tweets that do not involve the innovation concept experience a declining probability of earning likes. I hypothesize that users in 2020 who are interested in the idea of innovation are more likely to also like tweets that express positivity. A future study is recommended to validate the idea.

11. Conclusion

This study aims to find essential elements of food companies' tweets that help the companies to attract more likes, and thus to get higher attention in the competitive market. It is based on a dataset of 532,088 tweets by companies and organizations in the Canadian food sector. All Twitter data are collected using the Twint package and python coding. This study uses the number of likes as the dependent variable because the number of likes can reasonabally represent users' perceptions of each tweet and is a commonly used dependent variable in Twitter involved empirical studies. The focal independent variables consist of tweet sentiments, and a selection of common food claims and innovation terms mentioned in the tweets.

Despite being considered to operate in a sector with low innovations, food companies are constantly introducing new innovations. Besides product innovation and process innovation, companies also innovate in marketing strategies. Food labeling has been one way to help with the marketing of food companies' products and is believed to be efficient in leading food trends and innovations orientation in the future. Thus, this study shows that innovation-related terms do capture customers' attention and garner significantly higher number of likes.

By conducting Negative Binomial GLM regression analyses, this study partially supports Hypothesis 1 that positive toned tweets are more likely to earn likes. Unexpectedly, negative toned tweets are also positively correlated with the odds of getting likes, suggesting that outstanding tweets – whether positive or negative – are more popular than neutrally worded tweets. Hypothesis 2 is supported. This study thus recommends companies include urls, hashtags, photos, and videos in tweets to increase the possibility of getting likes.

The results fail to support Hypothesis 3 about the negative association between the length (number of words) of each tweet and the number of likes. Hypothesis 4 is partially supported by 2019 data that, tweets that contain keywords "organic," "new," "innovative," and "innovation" are helpful with more likes, different from keywords "kosher" and "food," which are expected to also help tweets to earn likes. Hypothesis 5 is mostly supported. Therefore, this study suggests food companies try not to include keywords "allergen," "preservative," "additive," "transfat," "cholesterol," and "sodium."

By comparing results of regressions running on 2019 and 2020 data, the coefficients of *innovative/tion* in all 2019 equations are positive. Also, even when the coefficients of all focal variables in the 2020 equation are negative, the coefficient of *innovative/tion* is still positive. An intuition can thus be made on the importance of the concept of innovation. Furthermore, besides the regressions running on all 2019 and 2020 data, this study also split 2019 and 2020 data into tweets that contain keywords “innovative” / “innovation” and tweets that do not. According to 2019 results, the keyword “organic” is showing negative impacts on the number of likes when the tweets contain keywords “innovation” and “innovative.” One reason can be customers’ aesthetic fatigue, meaning when companies in the market are pursuing the concept of “organic,” customers are less likely to pay attention to social media advertisements about “organic.” Based on 2020 results, positive tone, having urls and hashtags, including the word “gluten” in tweets are likely to increase the number of likes when the tweet contains keywords “innovative” and “innovation.” One hypothesis is that Twitter users who are interested in the concept of innovation may be more likely to be attracted by tweets that show a positive attitude, that include urls and hashtags, and that includes the keyword “gluten.” The study has provided extended research topics for future scholars to explore in the fields of food, food companies and customers, and food innovations.

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