This is the Pre-Published Version.

Munhyang Oh & Seongseop Kim (2021): Role of Emotions in Fine Dining Restaurant Online Reviews: The Applications of Semantic Network Analysis and a Machine Learning Algorithm, International Journal of Hospitality & Tourism Administration

This is an Accepted Manuscript of an article published by Taylor & Francis in International Journal of Hospitality & Tourism Administration on 13 Feb 2021 (published online), available at: http://www.tandfonline.com/10.1080/15256480.2021.1881938

Role of Emotions in Fine Dining Restaurant Online Reviews: The applications of Semantic Network Analysis and a Machine Learning Algorithm

ABSTRACT

This study attempts to investigate basic emotions incorporated in online reviews of fine dining Cantonese restaurants in Hong Kong and to investigate antecedents and consequences according to each emotion. This study adopts semantic network analysis and a machine learning algorithm to achieve its research objectives. A total of 2,118 reviews were used for the analysis. Five emotions – joy, sadness, disgust, surprise, and anger – accounted for 72% of prediction accuracy. Given that the five types of emotions in this study were closely associated with service, food, and reputation, the three components are considered the core elements of a fine dining restaurant experience. Results of this study imply that restaurants should understand customers' emotion based on big data analysis. The integration of emotion theory and practical implications can provide meaningful evidence on how to capitalize on big data.

Keywords: restaurant, online review, semantic network, text analytics, machine learning

Introduction

Cognitive appraisal theory proposes that subjective judgment of an event leads to emotional responses (Choi & Choi, 2019). Emotions are the outcome of subjective evaluation of a situation based on appraisal dimensions rather than being merely a product of cognition. In hospitality literature, studies on emotion related hospitality are limited despite the man-to-man service consumption nature of the hospitality industry. Studies related to emotion in the restaurant context treated emotion as one construct. Recent studies have examined valence in online reviews (Duan et al., 2016; González-Rodríguez et al., 2016; Oh & Kim, 2020; Xiang et al., 2017). However, valence is not enough to explain customer experiences. The final stage of appraisal is “social sharing” or verbal/non-verbal communication of emotions according to cognitive appraisal theory. Moreover, the intensity of emotions influences the amount of social sharing. However, only a few studies investigated whether this final stage of appraisal can be applied in the eWOM cases (Han et al., 2010). Knowledge on what type of emotions compels people to share their stories through eWOM is lacking in literature.

Based on previous studies on dining customers’ experiences and online reviews, several research gaps have been identified. First, even though emotion has been shown to be a determinant of valuable experiences and behavioral intention (Rimé et al., 1998; Serra-Cantallops et al., 2018; Standing et al., 2016), there is a lack of research on how and whether emotion explains diners’ consumption experiences. Second, most studies on emotion have been conducted using survey methods or experimental design (Han et al., 2009; Kim et al., 2016; Lin & Matilla, 2010). The analytical methods used have included structural equation modeling (Han et al., 2009; Kim & Choe, 2019; Ryu & Jang, 2007), regression analysis (Choe & Kim, 2019; Lin & Matilla, 2010; Teng & Chang, 2013), and linear mixed model (Kim et al., 2016).

However, these methods should be accompanied by an emerging academic and industrial trend: big data analysis using machine learning technology. This method offers new insights from massive volumes of data, compared to traditional analytic methods which have otherwise obtained via cross-sectional data and surveys. Thus, this study attempts to use textual data gathered from the Internet through a machine learning algorithm technique. The study first identifies the classification accuracy of this method for emotion-labelled data and clusters of emotional texts.

Third, although some studies have examined the role of emotions in restaurant experiences, most of them have measured emotions using only a few question items (Kim & Moon, 2009; Lim, 2014; Teng & Chang, 2013). However, emotions such as joy, sadness, surprise, anger, disgust, trust, fear, and anticipation are various and multifaceted (Plutchik, 1980). It is important to acknowledge the function of each emotion in order to understand customers' food consumption experiences more precisely. Thus, this study attempts to examine the antecedents of each emotion felt during a dining experience by investigating the content of online reviews according to each emotion. Fourth, even though the emotions embedded in stories of consumer purchasing experiences have been examined through text analytics using textual format data (Khan & Vorley, 2017; Laxmi & Pranathi, 2015; Michalski, 2014; Oh & Kim, 2020), few attempts to apply the concept of emotion to restaurant studies have been made. Thus, this study is designed to examine diners' restaurant experiences through text analytics of online review data.

Based on these research gaps, main objectives of the current study are threefold. The first is to identify the emotions hidden in online reviews shared by fine dining restaurant diners. The second is to uncover the patterns of diners' fine dining restaurant experiences presented in online reviews according to each emotion. The third is to compare the results of analyzing the semantic networks and keywords of customers' experiences presented in online reviews according to each emotion. This study features a literature review, methodology, findings, discussions and implications, and conclusions and suggestions for future studies.

Literature Review

Definition of Emotions and Basic Emotions

The human mind is composed of three discrete parts: cognition, emotion, and conation (Scott et al., 1979). Among them, emotion is the social expression of how people feel, and it is influenced by culture. Emotion has a strength with regard to subjective feelings (Ravi & Ravi, 2015). One of the traits of emotion is its nonlinear process, including feedback and interaction between emotion and cognition (Izard, 2009; Plutchik, 2001). Furthermore, emotion plays neurobiological roles in the evolution of awareness and the operation of mental processes (Izard, 2009). A follower of Darwin, Plutchik (2001) has shown the flows that can explain how sensory information is appraised and applied to actions or consequences.

Researchers have provided various classifications of basic emotions. "Basic" refers to emotions that pertain to value in coping with "fundamental life tasks" (Ekman, 1992, p.169). Based on robust evidence, many researchers seem to agree that six basic emotions are universal: fear, sadness, anger, disgust, joy, and surprise (Ekman, 1992; Izard, 2009; Lazarus, 1991; Plutchik, 2001). However, Plutchik (2001) proposes that there are eight basic emotions and organizes them in a wheel-like model, shown in Figure 1. The intensity of emotions increases from the outside to the center and opposite emotions are located on opposite sides of the wheel. The combinations of basic emotions are located between the basic emotions. For instance, love is a combination of joy and trust. Different kinds of positive emotions generate different types of objectives for survival, such as reproducing, having a sense of belonging, and investigating something new.

The first emotion is joy, which is an elevated state of pleasantness. Joyful people are likely to be confident and think they can control things with minimal effort (Tong, 2015). According to the result of appraisals, joy is positively linked with achievement and negatively linked with loss (Nezlek et al., 2008). The second emotion is trust. People experience trust when they cooperate in social exchanges (Nesse & Ellsworth, 2009). The third emotion is fear, which is a cue for physical danger and intensive anxiety (Scheff, 2015). In Smith and Lazarus's (1991) view, important appraisal elements of fear are "motivational relevant," "motivational incongruent," and "emotion-focused (low/uncertain) coping potential." Furthermore, danger/threat is the core relational theme of fear together with anxiety (Smith & Lazarus, 1993).

The fourth emotion is surprise, which arises from a sudden event and can have positive and negative valence (Talarico et al., 2009). Although surprise has different aspects, it is usually treated as a positive emotion associated with low certainty, high pleasantness, medium attentional activity, low anticipated effort, medium individual control, and high others' responsibility (Lerner et al., 2015; Smith & Ellsworth, 1985). The fifth emotion is sadness, which pertains to an uncertain loss with extremely unpleasant feelings (Plutchik, 2001; Smith & Ellsworth, 1985). Sadness also addresses goal failure and feelings of helplessness (Levine & Pizarro, 2004; Smith & Lazarus, 1993). The behavior of those experiencing sadness is similar to that of those feeling anxiety, but sad people prefer to choose a high-risk/high-reward alternative, whereas anxious people prefer to choose a low-risk/low-reward alternative (Raghunathan & Pham, 1999).

The sixth emotion is disgust, which is considered the most violent feeling (Menninghaus, 2003). According to Nesse and Ellsworth (2009), people feel disgusted when both parties fail to achieve a goal. Disgust is a sensory feeling such as hunger and tiredness, which help to prevent disease or death (Panksepp, 2007; Oaten et al., 2009; Rozin & Fallen, 1987). The seventh emotion is anger, which refers to the emotion related to hatred and is the motive for a variety of aggressions. Some scholars have argued that frustration is the primary cause of anger (Averill, 1983). Other studies define anger as a negative effect caused by frustration (Carver & Harmon-Jones, 2009). Anger is also treated as the opposite of fear (Lazarus, 1991) because people respond with either of those emotions when attacked by others. Major appraisal elements of anger are goal obstacles, blame toward others, unfairness, and low self-esteem (Kuppens et al., 2007). The eighth emotion is anticipation. It was initially introduced as a basic emotion by Plutchik (1980) and is the opposite of surprise. Interest is a form of anticipation with weak intensity, whereas vigilance is a form of anticipation with strong intensity. In neural science literature, interest has been interpreted as a core emotion to elucidate the effects of music (Salimpoor et al., 2011; Scherer & Coutinho, 2013; Vuust & Frith, 2008).

[FIGURE 1]

Cognitive Appraisal Theory

Cognitive appraisal theory proposes that subjective judgement of an event leads to emotional responses. Emotions are the outcome of subjective evaluation of a situation based on appraisal dimensions rather than being merely a product of cognition (Smith & Ellsworth, 1985). This theory is the dominant explanation for emotional experiences and was established with Arnold's proposal, which was subsequently developed. This theory overcomes the limitations of physiological approaches, which cannot explain what starts the process, and behavioral approaches, which fail to explain why people have different emotions in a similar situation and why emotions change (Roseman, 1984). The fundamental premise of this theory is that appraisals related to environmental aspects are critical for the well-being of organisms, and emotions are adaptive feedback that mirror these appraisals (Moors et al., 2013).

This subjective judgement is called “appraisal” (Smith & Ellsworth, 1985), which is a process that identifies and evaluates the importance of the environment for the satisfaction of concerns, such as needs, values, and goals (Moors et al., 2013). The four generally accepted prevailing appraisal dimensions are goal congruence, certainty, agency, and control. An example is the experience of a person watching customers next to his/her table (agency) making noise in a quiet upscale restaurant (goal incongruence) while not knowing (certainty) when they are leaving (control).

Appraisal theory involves primary appraisal, secondary appraisal, and social sharing. If an event is goal relevant, then people can feel emotions, and when this emotion is congruent with their goals, it generates positive emotions. This stage is called “primary appraisal,” in which emotions are determined as good or bad (Zajonc, 1980) and is an unconscious stage of the human mind. Secondary appraisal is the stage of response wherein individuals think of the outcome of their behavior as a response, which is a phenomenon called “core relational theme” (Lazarus, 1991). Studies on appraisal have pointed out the potential bias of memory-reporting and have attempted to determine the real causes of emotions. According to the results, appraisals may be linked with more than one emotional response (Nezlek et al., 2008) and can differ among individuals depending on personality (Power & Hill, 2010), cultural variation (Imada & Ellsworth, 2011; Mesquita & Ellsworth, 2001; Roseman et al., 1995), and other factors. The third stage of appraisal is social sharing or verbal/non-verbal communication of emotions (Fussell, 2002; Rimé et al., 1998; Sauter, 2017). An experimental study on the social sharing effect of negative emotion through exposure to different intensities of films revealed that the intensity of emotions influences the amount of social sharing (Luminet et al., 2000), except for shame and guilt (Rimé et al., 1998).

Empirical Studies on Emotions in the Tourism and Hospitality Literature

One of the studies that applied cognitive appraisal theory focused on the emotions of luxury cruise tourists (Manthiou, Kang, & Hyun, 2017). The above study used four appraisal dimensions, namely, goal congruence, certainty, novelty, and agency, and employs script theory that describes the relationships among recollection, storytelling, and behavior. It posits that appraisal leads to discrete emotions that affect the recollection of memory and storytelling about products and services, and these two factors result in repurchase intention. All proposed paths were supported, except for the following three paths: certainty to negative emotion, novelty to positive emotion, and negative emotion to storytelling. The results showed that goal congruence is the most important appraisal dimension for explaining emotions in this context. Furthermore, certainty leads to positive emotions in the luxury trip context (Manthiou et al., 2017).

Other studies in tourism adopted cognitive appraisal theory to investigate delight in the theme park context (Ma, Gao, Scott, & Ding, 2013) or memorable food tourism (Kim, Badu-Baiden, Oh, & Kim, 2020). Ma et al.'s (2013) study tested causal links between appraisal variables, including appetitive goal congruence, goal importance, goal interest, and unexpectedness and delight. All four dimensions were supported as antecedents of the delight of theme park tourists. A study of Ma et al.'s (2013) also deemed the level of satisfaction as a degree of goal realization and concludes that design stimuli for deriving delight and segmentation on the basis of motivation are useful marketing strategies in theme park management from the perspective of hedonic experience providers.

In the hospitality literature, many studies utilized emotions, such as surprise (Kim & Mattila, 2010), pleasure (Lin & Mattila, 2010; Ryu & Jang, 2007), arousal (Wirtz, Mattila, & Tan, 2000), anxiety (Kim et al., 2016), regret (Kim et al., 2016; Zeelenberg & Pieters, 1999), disappointment (Zeelenberg & Pieters, 1999), and anger (Kim et al., 2016). From the view of evolutionary psychology, Plutchik and Kellerman (1974) proposed the eight kinds of basic emotions including fear, anger, sadness, disgust, joy, acceptance, surprise, and expectancy, whereas Richins (1997) proposed emotions consisting of anger, discontent, worry, sadness, fear, shame, envy, loneliness, and romantic love.

The stimulus–organism–response (S–O–R) model (Figure 2) is a framework that aims to describe the sequential chain rules among environmental stimuli, emotional states, and responses or behaviors (Kim & Moon, 2009; Lim, 2014; Lin & Mattila, 2010; Peng et al., 2017). For example, restaurant ambiance (interior, music, smell, and authenticity) affects customers' emotional responses, which in turn affect various aspects of their overall evaluation, including their satisfaction, revisit intention, WOM, and recommendation (Bitner, 1992; Kim, Song, & Youn, 2019; Ryu & Jang, 2007).

[FIGURE 2]

Other studies pertaining to emotions examined the relationship between emotions and consequences, including satisfaction, behavioral intention, and restaurant image, without presuming any stimulus (Baker & Kim, 2019; Chen et al., 2014; Han et al., 2009; Mattila, 2000). Kim et al. (2016) investigated the relationship between stimulus and emotions to examine the effect of "waiting in a restaurant" on customers' emotional reactions by conducting a simulation experiment. They found that anxiety and anger are the emotions perceived by customers when waiting in a restaurant (Kim et al., 2016). Gross (2008) investigated the effects of waiting on anxiety, anger, and regret by applying the emotion regulation process model and suggested customer emotion regulation strategies for different stages of waiting (e.g., attentional deployment and suppression strategies for post-process waiting and reappraisal strategy for in-process waiting).

Methodology

Data Requirement and Data Source

Figure 3 shows the research flow. First, to collect data on fine dining Cantonese restaurant experiences in Hong Kong, this study gathered online reviews from TripAdvisor.com by using the automated parsing software Webharvy. Owing to its large number of restaurant reviews and high likelihood of exposure to travelers, TripAdvisor.com has become an important platform for restaurant marketers and customers. We considered a total of 7,724 online reviews of Cantonese fine dining restaurants published on TripAdvisor.com from January 2014 to June 2018 as the data source. However, this study randomly selected only 2,118 online reviews for the analysis by using the "rand" function of MS Excel after deleting short reviews and those with excessive personal stories.

[FIGURE 3]

Second, this study conducted an emotion labeling survey, as shown in Figure 3. We conducted the online survey in January 2019 to label each review in accordance with its embedded dominant emotion. Given that the judgment of emotions in reviews by one or a few people can lead to bias, even if they are experts in linguistics, this study adopted a rule of agreement on the labeling of emotions with 10 people. An inclusion of six reviews in one questionnaire was appropriate considering the durability of concentration. Hence, we included six reviews in one e-questionnaire and distributed each set to 10 people. Qualtrics.com was used to administer a web-based survey comprising a total of 740 sets (with six questions each) of e-questionnaires, which were distributed to 7,400 respondents via Amazon MTurk. We selected respondents aged 21 years or older in the U.S. considering their level of comprehending vocabularies and concentration. The respondents were required to identify a maximum of three basic emotions for each restaurant review. After identifying dominant emotions for each review, we discarded cases with two or more dominant emotions. After excluding online reviews with mixed emotions that could not be categorized into one emotion, we used a total of 2,118 reviews for data analysis.

Data Analysis

As shown in Figure 3, we performed text classification by using support vector machine (SVM). Then, we identified basic emotions in fine dining restaurant online reviews and classified documents in accordance with the identified emotions. Semantic network analysis and clustering to explore antecedents and consequences of each emotion were implemented. The data used for this study included the reviewer's name as well as the title, date, and text of the review. Since terms used to describe emotions in English differ from those in other languages (Wierzbicka, 1992), translation may distort the original meaning. Therefore, reviews in languages other than English were not considered in this study. NodeXL and python were used for data analysis. NodeXL, which is an open-source MS Excel template, is normally used for social network analysis and content analysis. It was used to explore network graphs. Semantic network analysis was conducted by using words as vertices. Python, a type of programming language which is used for web development and system scripting, was applied for text classification because of its ease of code readability. The data analysis process was modified from Tripathy et al. (2016). The proposed approach to text classification is as follows. Step 1 is "performing pre-processing" and step 2 is "preparing the training dataset with a bag of words for each emotion." Step 3 is "transforming into a matrix of numeric vectors," step 4 is "treating matrices as inputs for supervised machine learning classification," and step 5 is "comparing the accuracy of the methods."

The multiclass support vector machine algorithm was applied because it had previously been shown to have high accuracy compared to other methods (Aman & Szpakowics, 2007; Kim and Kwon, 2011). It has the advantage of preventing the overfitting problem (Wang & Xue, 2014), which causes noise and has a negative impact on the performance of new data. SVM basically separates two classes with a maximized margin using a separating hyperplane, whereas multiclass SVMs can be used for the categorization of three or more classes (Wang & Xue, 2014). When the SVMs optimize the problem, a hyperplane separates the classes as follows:

$$wx + b = 0 \tag{1}$$

x: An object to be classified;
w, b: The vector from a training set.

In order to solve a linearly constrained quadratic programming problem, SVMs provide the solution with constraints $[y_i(x_i w\varphi + b) \geq 1 - \xi_i, \xi_i \geq 0, i = 1, \ldots, l]$ in order to cause optimization, as follows (Wang and Xue, 2014; Zhang et al., 2008):

$$\min_{\omega} \frac{1}{2}\omega^2 + C\sum_i \xi_i \tag{2}$$

ω: Weight vector;
C: The regularization constant;

φ: The mapping function, which moves the training data into a suitable feature space in order to allow for nonlinear decision surfaces;
ξ: Margin constraints.

Network analytics refers to link mining, the discovery of links among nodes of a network to identify the relationships among subjects (Lim et al., 2013). Numerous basic technologies make network analytics feasible, such as bibliometric analysis, citation networks, co-authorship networks, social network theories, network metrics and topology, mathematical network models, and network visualization (Chen et al., 2012). The network analysis literature has examined degree centrality (DC) as a way to recognize the influence of nodes in a network. DC refers to the number of direct ties a word has. The higher the degree a word has, the more influential it is in the network. The "g" in the following equation represents the number of pairs of vertices in the network.

$$\text{Normalized DC} = \frac{1}{g-1} DC \tag{3}$$

Results

Identification of Emotions in Online Reviews

First, three emotions – anticipation (7 reviews), fear (3 reviews), and trust (120 reviews) – were deleted because of a very low number of reviews and 0.00 precision in the results of initial SVC classification. The accuracy of the initial classification algorithm using 33% of the test set was 0.67. Table shows the final labelling result, the precision, recall, and F1-score of the final classification results. The accuracy of the final classification algorithm using 33% of the test set was 0.72. The accuracy level was similar to those of other studies (Aman & Szpakowics, 2007;

Bhaskar et al., 2015; Bhowmick et al., 2009; Kim & Kwon, 2011; Patil & Patil, 2013). Five basic emotions in total were noticed: joy, sadness, disgust, surprise, and anger.

[TABLE 1]

High-centrality Words

Table 2 reports the centrality values for the semantic networks of each emotion. According to the results of checking the normalized degree centrality values, some similarities and differences across the classified emotions were identified. In semantic networks, several words including "food," "restaurant," and "service" were commonly influential for all five emotions. However, distinct differences also existed. In the joy network, "best," "excellent," "time [several experiences]," "well," and "experience" were observed to be keywords. In the sadness network, "dinner," "disappointed," and "time [service timing]" were shown as important. In the disgust network, "rice," "quality," and "tasting" were identified as influential words in the network flow. In the surprise network, "course," "wine [well-matching with food]," "view," and "high" were found to be impactful words in the network flow. Finally, in the anger network, "table [unprepared service]," "never," "lunch," "asked," "ordered," "time [waiting time]," "staff," and "served" were the influential words.

[TABLE 2]

Joy

The joy emotion network revealed 118 distinct clusters which differed in size, but only five salient clusters were selected. Clusters were named by analyzing words in the clusters as well as the sentences or documents with those words. Cluster 1 included words specifying "great service and Victoria harbor view." Many vertices described satisfactory service, such as "excellent," "best," "nice," "great," "good," "memorable," and "wonderful." Vertices regarding views were included variants such as "view," "views," and "Victoria [name of harbor located in Hong Kong]." The following is an example of a review illustrating the joy emotion attributed to the impression of Cantonese fine dining restaurants in Hong Kong.

> *"Situated on the 25th floor of the M hotel this Michelin rated restaurant is great. The atmosphere, the views over Hong Kong harbour and the staff are excellent. …… The evening was relaxing and very enjoyable. Highly recommended but suggest to book as the restaurant was full the night we went even though it was early in the week."*

Cluster 2 contained words relating to "delicious and traditional dishes." Many vertices represent dishes in the restaurant, such as "peking," "food," "tasting," "signature," and "dishes." Some adjectives were used to describe the characteristics of dishes, such as "delicious," "traditional," and "impeccable." The following is an example of review that described the dishes.

> *"A friend of mine recommended me this places and I am greatly thankful to him, was one of the best Cantonese meals I had. The traditional essence is present in every dish, the flower crab was by far my favorite and the service is very attentive too. I recommend this place without a doubt!!"*

Cluster 3 comprised words illustrating "various ingredients and recipes." Many vertices in cluster 3 addressed ingredients such as "pork," "goose," "chicken," "foie gras," and "egg," as well as recipe types such as "bbq," "fried," "roast," and "stir." The following is an example of a review that addressed various ingredients and recipes.

> *"Enjoyed the turnip cake with the XO chili sauce, deep fried spring roll with shrimp, steamed barbecue pork buns, the steamed buns with mushrooms, the rice flour rolls stuffed with barbecued pork…… Eager to go back and try other items on their menu!"*

Cluster 4 included words accounting for "high reputation with Michelin stars and location." Several vertices were related to the reputation of the restaurant, such as "Michelin," "star," and "starred." There were also location-related words like "hotel" and "Kowloon [an area in Hong Kong]." The following review is characteristic of cluster 4.

> *"If you would like to experience a Michelin restaurant this is certainly a very recommendable restaurant to go to."*
>
> *"Just like any Michelin Starred restaurant should, the place definitely exceeded my expectation."*

Cluster 5 contained words regarding "private seats and request handling." Vertices in cluster 5 included "private," "window," "table," "seated," and "request." The following are examples of reviews in cluster 5.

> *"Great food and service -- and it has some great private rooms and areas. Perfect for a celebration or meeting."*
>
> *"Highly recommend getting a booking here and requesting for a seat next to the windows so you can dine with a view! Although not necessary as no matter where you sit the giant window panes allow to look out wherever you sit."*

The results of the networking of the joy emotion after combining intergroup edges are showcased in Figure 4.

Sadness

The sadness network revealed 64 distinct clusters of various sizes. However, only the four biggest clusters were chosen for this study. Cluster 1 included words relevant to "poor and disappointing service/food." Vertices in this cluster showcase the evaluation of service or food, using words such as "poor," "average," "ok," and "disappointed."

> *"A friend recommended N. … We gave it a try and found the restaurant overpriced and the staff was very unfriendly and unhelpful."*
>
> *"Come for a nice relaxing meal but there are many dim sum restaurants in Hong Kong serving better food."*

Cluster 2 contained words regarding “dissatisfaction in signature dishes.” Vertices in this cluster described signature or main dishes in the restaurants. The following reviews are examples.

“I had the chef's signature menu and every dish was terrible. Don't waste your money here.”

“Its gold signature fried rice was poor as it was bland.”

Cluster 3 included negative expression regarding “high price charged.” Many vertices indicate high price, such as “price,” “high,” “paid,” and “charging.” Many reviewers exhibiting the sadness emotion felt that the restaurants were low value for money. The following reviews exemplify cluster 3.

“Unfortunately we felt that the food did not match this high standard. … The wine list is very pricey. … I suspect that this is somewhat a tourist menu …… Unfortunately we will never know.”

“Price/Value: Very expensive, but more importantly, unjustified. The food was above average, but was not sufficiently special or creative or delicious to warrant these lofty prices.”

“Main dishes had small servings and were overpriced.”

Cluster 4 contained words showing “disappointment compared to expectation/reputation.” As shown by the statements below, vertices in this cluster highlighted disappointment and restaurant reputation.

“At three Michelin Stars, a restaurant should be an experience as well as a place where the food and service is exceptional. But … the lack of personality and well timed service was disappointing.”

“The food was average! My local Chinese restaurant is at least as good, if not better. Overall very disappointing, considering the excellent Trip Advisor reviews.”

As a result, Figure 4 illustrates the network visualization of the sadness emotion.

Disgust

The disgust network revealed 54 distinct clusters which varied in size. However, the four biggest clusters are presented here. Cluster 1 included words regarding “terrible quality and expensive dishes.” Many vertices in cluster 1 manifest disappointment regarding quality, such as “insult,” “average,” “worst,” “terrible,” and “disappointed.” The word “expensive” was also common, indicating that the dishes offered low value for money. Compared with the sadness network, the disgust network revealed more aggressive and lamentable dissatisfaction. The review below is exemplary of cluster 1.

> *“Considering the quality of the food and the price, this restaurant is not at all recommendable. I would call it a typical tourist trap.”*

Cluster 2 contained words associated to “good reputation but the worst meal.” Many vertices in this cluster addresses the good reputation of restaurants, including “Michelin,” “star/stars,” “rating,” and “best.” At the same time, bad experiences were implicated by words such as “worst” and “insult.” Such reviews are typified by the following examples.

> *“Food is no more than average. ... Don’t waste your money on this restaurant. Plenty more to discover in HK. Very disappointed to have wasted one evening in HK at this restaurant.”*

> *“To add insult to injury; I had stomach upset after eating the dinner and have to retired to the toilet twice! Price / performance was very poor....”*

Cluster 3 included words regarding “bad handling in general.” According to the sentences with vertices in cluster 3, bad service experiences were expressed in ways similar to the review below.

"We had a six course tasting menu and the service was so rapid, that we were finished in 45 minutes. There were times they served 3 courses at the same time. And even though we asked them to slow down, they did not. They knew we were celebrating, yet there was no mention of it."

Cluster 4 contained words regarding "low value for money and no intention to revisit." Vertices in cluster 4 indicated no intention to revisit and sentences with vertices regarding value and money showed that the reviewers perceived the food they consumed to be low value for money. For example,

"On the up side if there is one the food was very tasty though very small even for Hong Kong, my opinion you would get better value for money at a street stall."

"The location and the setting of the restaurant were good. However, given the price and the quality of the food, it's bad value for money. Not recommended at all."

The network visualization of the disgust emotion is displayed in Figure 4.

Surprise

Even though the surprise network revealed 71 distinct clusters, the four biggest clusters were chosen. The surprise network appears confusing because of the nature of surprise that can contain positive and negative valence (Talarico et al., 2009). Clusters in the surprise emotion showed positive and negative emotions.

Cluster 1 included words concerning "special selection and tasty dishes." Many vertices in cluster 1 indicated a positive view of experiences, such as "good," "quality," "nice," "special," "excellent," and "tasty."

"Fascinating meal. Decided to have a blow-out and really go for it with a 7 course sampling menu. Not being experts we believe this is quite specialized, modern Chinese dining."

"For such a fine restaurant, I was surprised at the selection. The menu was extensive offering all your favorite classics as well as exotic and unique dishes. I am not as risky, so I had the lemon chicken and it was the best I have ever had."

Cluster 2 contained words regarding "high-priced meal." The vertex "bill" indicates situations in which high-priced or unwanted meals were served in fine dining Cantonese restaurants in Hong Kong, leading to surprise. Such instances are exemplified by the following reviews.

> *"Bill for 2 including a couple of beers & glass of wine was about US $130."*
>
> *"One thing I found interesting, while we were waiting for our dishes to come, they brought out some peanuts (I can't remember if they were roasted or steamed) to munch on. ... we found we were charged for them on the bill. Didn't ask for them and didn't eat much of them (wish I had now) (also my partner has a peanut allergy) so had a bit of a surprise there."*

Cluster 3 included words specifying "good wine pairing." Vertices in this cluster, for example "list," "pairing," and "bottle," were about wine. Reviews associated with wine showcased good experiences with wine pairing, as demonstrated below.

> *"We also selected the wine pairing - this was great and we all felt spoiled with the great selection and the good stories from the enthusiastic sommelier..."*

Cluster 4 comprised words regarding "rude staff and small portion of food." Vertices in cluster 4 highlighted poor staff service delivery and the small size of portions.

> *"The problem that I had with B is the service. The staff were not engaging, not helpful and not proud of their restaurant. They were merely there to take you order, and serve you your meal. ... He wasn't unfriendly, but rather, just not engaging."*
>
> *"Aside from a first course of stuffed whelk, which was delicious, and the crust on a very small tart at the end, there was nothing about our meal here that was of any interest at all."*

The networking of the surprise emotion is exhibited in Figure 4.

Anger

The anger network revealed 68 distinct clusters, but only four dominant clusters were chosen. Cluster 1 encompassed words manifesting "terrible experience in high-rated restaurants." Many vertices in cluster 1 were adjectives or verbs with negative meanings, such as “terrible,” “poor,” “bad,” mediocre,” and “shocked.” For example,

“Service is terrible. Ordered 2 steamed rice and got 1 - waiter said only ordered 1 and started arguing with me … Taste is mediocre at best and the steamed chicken was cold. Service as reiterated is better at a food stall and the quality of the food vs price is way better at other similar restaurants. … Nightmare!”

“After the fuss over mix up and the poor handling, to be honest food quality and experience was lost on our group. Never again and shocked at the experience given the reputation of the restaurant and other associated venues on the HK F&B scene.”

Cluster 2 contained words regarding “mediocre quality and expensive food.” One vertex in cluster 2 was “quality,” whereas other vertices were adjectives such as “ok,” “mediocre,” “best,” “nice,” and “average.” “Expensive” addressed a high level of food price compared to its perceived value. Reviewers expressed anger when they felt that they had received food that was mediocre despite its high price.

“… They charged for everything. They are ridiculously calculative. … There are many better places to eat in hk.… I had congee with liver. It was only passable. I had some fish Maw thing which is totally bland. That was why I asked for cut chillies. It never arrived. I wasted my time at this place. You have been warned.”

“We were graciously escorted to our table and dishes of cashews were placed at the table and then replenished (without any request). Needless to say, we were charged for this!! … We placed our order. But then the manager came over with a platter of beautiful prawns that we did not order. He encouraged us to taste them - saying we could cancel our order and have this instead. … Then we got our ordered food - and then the bill. … Outrageous!!!”

Cluster 3 encompassed words related to “slow service.” Vertices in cluster 3 represented time, for example “time,” “last,” “next,” “half,” “day,” and “hour.” Reviews with those vertices indicated slow service triggering feelings of anger.

“They took our credit card away from us and took literally half an hour to bring it back. We ended up coming home late and forgetting the food because we were overall annoyed. … I will never repeat the experience.”

Cluster 4 included words regarding “bad handling,” describing poor/ugly situations diners encountered. Online review writers showed feelings of anger resulting from bad service. The following review is an example.

> *“Took 6 people for a business lunch. Was ushered into an ad-hoc semi private room in the back of the cavernous restaurant. Upon being seated we were ignored for 10 minutes. Management scraped the bottom of the barrel to find this collection of dim witted, broken toothed, non-English speaking serving staff. Their laughable Ming dynasty stage prop uniforms are stained and in tatters.”*

Figure 4 shows the network visualization of the anger emotion.

[FIGURE 4]

Discussions and Implications

In order to investigate the underlying analogies implicating reviewers’ fine dining restaurant experiences, semantic network analyses across each emotion were carried out. Important findings and implications are as follows.

First, this study contributes to theory development because this study initially introduced cognitive appraisal theory to online review analytics. Most previous studies on analyzing online reviews did not adopt theories but reported results generated using text analysis programs (Racherla et al., 2013; Wang et al., 2018 Xiang et al., 2017), By applying the theory, restaurant patrons’ eWOM-generating behaviors may be better understood. In addition, this study capitalized on the theory of emotions to explore online reviewers’ subjective evaluation regarding fine dining restaurant experiences through textual data analysis. The findings indicate that subjective judgement of emotions encountered by customers were expressed as generating eWOM feedback about Cantonese fine dining restaurants in Hong Kong. Results of analyzing emotions can be utilized to demonstrate academic and practical implications. In addition, since this study employed both semantic network analysis and a machine learning algorithm it is more advanced compared to most previous studies which utilized only semantic network analysis.

Second, this study is the first attempt to identify five basic emotions that manifest in online reviews of restaurants. Joy was the dominant emotion; reviewers are likely to generate online reviews when they perceive their food consumption experience to have had high hedonic value. This indicates that obtaining hedonic value from food consumption experiences can be an underpinning motive for visiting fine dining restaurants. This result is in line with those of previous studies (Chen & Peng, 2018; Lim, 2014; Nejati & Moghaddam, 2013; Peng et al., 2017). Therefore, restaurant managers need to deliver experiences with high hedonic value by offering traditional dishes using various ingredients and recipes and handling request professionally in order to generate positive eWOM.

Third, there were some differences in words having high centrality among emotion networks, meaning that influential words in the network flow were different among networks. Keywords in the joy network were pertinent to overall quality, while keywords in the sadness and anger networks pertained to slow service and rude staff. Keywords in the disgust network were relevant to mediocre food and high price, while keywords in the surprise network represented good view and wine pairing with course menu. The results showed that some aspects generated only positive emotions, whereas others generated only negative emotions. For example, view, wine pairing, private seats, and location are closely associated with only positive emotions, whereas price is linked with only negative emotions. This finding is in line with Herzberg's two-factor theory (Herzberg, 1966; Kim et al., 2016; Oh et al., 2019), which addresses the existence of both "satisfiers" and "dissatisfiers" in assessing customers' satisfaction. Thus, to improve restaurant customers' satisfaction, restaurant managers need to work on reinforcing "satisfiers" through new/unique tactics such as wine pairing menu development. In addition, they need to dissipate "dissatisfiers" through preventing the provision of neophobic food, staff having impolite manners, and the enforcement of in-house dining culture.

Fourth, all types of emotions in this study stemmed from service, food, and reputation. Moreover, favorable or unfavorable evaluations coexisted in the main components. Results of the textual analytics are conducive to understanding kaleidoscopic emotions as perceived by patrons of fine dining restaurants. Clusters that emerged according to five emotions indicate salient components of each emotion that customers encounter while dining. Since reputation showcases expectations of fine dining restaurant customers (Chang, 2013; Ha & Jang, 2012), restaurant managers need to meet their standards by providing high quality food and preventing bad handling.

Fifth, price was mainly associated with the sadness, disgust, surprise, and anger emotions, and not with the joy emotion. In particular, low value for money represents the disgust emotion. This is because value for money is one of the important motivations of consumers' restaurant experiences (Lin & Mattila, 2010; Mattila, 2001). The major issue raised by reviewers regarding the price of fine dining restaurants in Hong Kong was that some restaurants were so calculative that they charged for condiments or small side dishes. Therefore, charging for snacks, side-dishes, or unordered starters should be refrained from since it generated negative emotions in most cases. Another issue raised by reviewers was that the experience did not justify the high price they paid for it. Thus, restaurant managers need to make an effort to provide value for money by offering special or memorable experiences by holding events with unique themes, celebrity encounters, or wine tastings at a discounted rate, or by inviting guest chefs/bartenders.

Sixth, location and private seats were linked to augmenting the joy emotion only. As previous studies have argued, location plays a key role in appealing to customers and enhancing loyalty by creating positive emotions (Chen & Tsai, 2016; Chen et al., 2014; Han et al., 2009). A location is not only the geographical region of a restaurant, but also its situation regarding traffic, accessibility, visibility, and convenience of parking. As the results show, the private seating arrangement was a pivotal factor in heightening the joy emotion. Since diners seek privacy while visiting restaurants (Hwang and Yoon, 2009), fine dining restaurant managers need to arrange table layouts scrupulously because fine dining restaurants are places for business meetings and intimate dates. For example, establishing cubicle seating or installing partitions need to be considered in order to offer more privacy to customers.

Seventh, the importance of wine pairing in generating the surprise emotion was highlighted because wine pairing menus offer a special gastronomic experience to customers in a sense that serving cuisine accompanied by wine leads to memorable dining experiences (Harrington and Seo, 2015). With this in mind, the wine pairing effect can be realized by hiring qualified sommeliers and educating service staff.

Eighth, reviewers demonstrated a strong association between their intention to revisit and the joy and disgust emotions. The disgust network comprises both food with low quality and words such as “never,” “go,” “back,” and “again.” In a similar manner, the joy emotion is associated with words such as “recommend,” “definitely,” “come,” and “back.” According to the results, the disgust emotion resulting from low quality of food consequently leads to discouraging customers’ intention to revisit. This result is in line with those of previous research, that food quality is the most important factor in facilitating future intention at full-service restaurants (Chen & Peng, 2018; Sulek & Hensley, 2004; Namkung & Jang, 2007). The findings of this study are summarized in Figure 5.

[FIGURE 5]

Conclusions and Suggestions for Future Study

This study attempted to analyze basic emotions shown in online reviews of fine dining Cantonese restaurants in Hong Kong. Five types of emotion – joy, sadness, disgust, surprise, and anger – were identified as a result of text classification. For example, "joy" was the most salient emotion in the reviews, indicating that customers seek benefits from consuming reputable food and service. All five types of emotion in this study were closely associated with restaurant service, food, and reputation, rather than whether the emotions were good or bad. The results indicate that diners perceived service, food, and reputation as core aspects of fine dining restaurant experiences. Interestingly, location and private seating were closely related to the joy emotion, while good view and wine pairing were closely related to the surprise emotion. In addition, intention to revisit was greatly affected by the joy and disgust emotions.

This study is vulnerable to some limitations. First, this study employed the multiclass support vector machine algorithm for text classification. Future studies need to adopt other algorithm methods and then compare the results of this study to those generated through different methods. Second, types of emotion vary according to different scholarly definitions of emotions (Izard, 2009; Lazarus, 1991), and this study focused on Plutchik's (1980, 2001) circumplex emotion model. Thus, future research needs to compare the results of this study with those accruing from employing other classifications. Third, classification performance of "surprise," “disgust,” and “anger” was relatively low because the reviews of Cantonese fine dining restaurants in Hong Kong were very positive and thus highly biased toward “joy.” The concern was similar to those of online review studies that reported skewness attributed to more positive answering on online reviews rather than unfavorable answering (Racherla et al., 2013; Wang et al., 2018). Further, this pattern is similar to the argument that respondents tend to show a high level of satisfaction or positive emotion in a fine dining restaurant customer survey (Han et al., 2010; Nejati & Moghaddam, 2013; Serra-Cantallops et al., 2018). Therefore, a subsequent study is necessary to identify whether the results of this study are cogent compared with studies conducted in other regions or countries.

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